How Do Large Epidemics Redistribute Market Power? Evidence from the 2003 SARS Shock in China*

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Abstract

Market power is costly to build and, once established, it is typically persistent and difficult to change. This paper investigates the impact of large economic shocks (serious epidemics) on the redistribution of market power in manufacturing industries. Our model of firms' dynamic decisions on production, pricing, and inventory demonstrates the importance of inventory stock and demand uncertainty to understand market power and implies a new measure of market power. We find that the 2003 SARS shock in China significantly reduced the market power of firms in the SARS-impacted areas, relative to others. The effect is long lasting. SARS also substantially increased the inventory and demand uncertainty of SARS-affected firms relatively, which contributed partially to the redistribution of market power.

Keywords: *market power, epidemics, inventory, SARS*

JEL classification: *D2, L1, L2*

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1 Introduction

Market power plays a vital role in various fields of economics, by influencing social welfare, resource allocation, and economic development.[1] It is also an important factor that shapes firms' heterogeneity in behavior and competitiveness (e.g., Bresnahan, 1989; Berry et al., 2019). While it is costly to build, market power is typically persistent and hard to change. This paper examines the impact of large economic shocks – severe epidemics – on the redistribution of market power across firms. During epidemics and pandemics, the fear of infection, together with government policies to fight against diseases, may change the consumption habits of consumers and the production/trading decisions of affected firms, potentially reducing these firms' market power and competitiveness. In addition, large epidemics and pandemics almost always lead the affected manufacturing firms to accumulate inventories, which pressures the affected firms to reduce prices. This paper examines the impact of severe epidemics on the redistribution of market power and investigates the role of inventory in the process, using the 2003 Severe Acute Respiratory Syndrome (SARS) epidemic in China as a natural experiment.

To understand the role of inventory and demand uncertainty in market power, we develop a model to describe firms' dynamic decisions on production, pricing, and inventory in the presence of demand uncertainty. The model borrows from Kahn (1987) that firms make production and pricing decisions dynamically to maximize the long-run payoff, by trading off the stockout probability and costs of inventory and production facing uncertain demand. We extend Kahn's model to accommodate flexible markup, by allowing for flexible production and inventory costs together with a flexible demand function. The model predicts that a higher level of inventory reduces market power: because firms cannot fully adjust production to offset changes in inventories given variable production and inventory costs, higher inventory stock pressures firms to cut prices and reduce markup. Moreover, higher demand uncertainty requires firms to produce more and hold more inventory to buffer against stockout if the

[1] Some examples include De Loecker et al. (2020); Autor et al. (2020); De Loecker and Warzynski (2012); Hsieh and Klenow (2009); Syverson (2019); Edmond et al. (2023).

production cost function is not too convex, which increases supply costs and reduces markup. This result is confirmed empirically in a large panel of Chinese manufacturing firms. It also echoes the findings of Aguirregabiria (1999) who theoretically and empirically shows that higher inventory holding reduces firm markup based on an (S,s) model of the retail industry.

The model demonstrates the necessity of accounting for the heterogeneity in inventory stock and demand uncertainty to understand market power. When there is inventory heterogeneity and demand uncertainty, the traditional measure of market power — referred to as raw markup hereafter and defined as the ratio of output price to the marginal production cost — does not capture firms' true markup. This is because inventory causes a difference between sales and output (footnote 11 in Bond et al., 2021), affects endogenous pricing and production decisions, and, more importantly, makes production and pricing decisions dynamic. Our model provides a straightforward measure of markup to correct this problem, by conveniently adjusting the raw markup with a term that captures the probability of stockout. This improves the literature on the measurement of markup using the production function approach (e.g., Hall, 1988; De Loecker, 2011; De Loecker and Warzynski, 2012; Raval, 2023).

We use a difference-in-differences analysis to examine the impact of SARS on market power, utilizing the fact that SARS influenced some provinces much more than others in China.[2] We find that the SARS redistributed market power substantially from the SARS-affected firms to firms in other areas. It reduced the average markup of firms located in the four provinces that were hit hardest by SARS by 7.8 percentage points, relative to other firms. The impact is long-lasting. After the initial drop by 5.5 percentage points in 2003, the decline in markup accumulated to 13.8 percentage points in 2007 relatively for firms in the SARS-affected areas. This suggests that although the epidemic shocks are temporal, they may have long-lasting

[2]Our estimated SARS effect contains the direct effect of the epidemic and the induced policies to fight against it. Although the prefecture-level data on SARS and other variables are publicly available, the province-level analysis is more appropriate for at least two reasons. First, the policies for infection prevention and control of epidemics are implemented at the province level in China. Second, the within-province market in China is more integrated compared with cross-province regions. So if SARS affected a prefecture or if the government implemented a lockdown at the province level, the whole province would be seriously affected. As a result, analysis based on within-province variations is likely to understate the true SARS effect.

effects on market power, presumably because they may change some fundamental factors such as consumer preference, demand uncertainty, and firms' production and inventory strategies. Moreover, market friction exists and it may be hard for firms to recapture the lost consumers after the shock. As supporting evidence, we observe a long-lasting decline in the market share of firms in the SARS-affected provinces. We also provide an external validation of the impact of SARS on market power using the province-level producer price index (PPI).

Inventory and demand uncertainty played an important role in driving the impact of SARS on the redistribution of market power. SARS increased the average inventory ratio by 1.4 percentage points (an 11% increase) and demand uncertainty by 14% of a standard deviation for firms in the SARS-impacted provinces relatively. Similar to markup, the effects are long-lasting. As a mechanism, the increase in both contributed to a reduction of markup by 2 percentage points (or 26% of the SARS effect) in our decomposition. To our knowledge, this is the first firm-level evidence on the important role of inventory and demand uncertainty in driving the large impact of epidemics/disasters on market power.

We provide two independent pieces of evidence to strengthen the causality analysis. The first evidence uses the differential timing of the SARS outbreak in Guangdong and other provinces. The second uses the cross-province variation in the severity of the shock to test the heterogeneous effect of SARS in different provinces. As expected, we find that the SARS effect emerged earlier in Guangdong and SARS had a much larger impact on firms located in provinces that were hit harder by SARS, providing further support to the causal effect.

The impact of SARS is heterogeneous across locations, industries, and firms. The effect is larger in industries that produce final than intermediate goods, and for firms that are larger and had higher markup before the shock. Moreover, the neighboring provinces of SARS-affected areas benefited with increased market share and market power and reduced inventory. Our results are robust in a series of robustness checks. These include using alternative markup measures, controlling firm fixed effects, using alternative inventory measures, using an alternative classification of treated provinces.

Finally, we explain the SARS effect mainly as a demand shock from the firm's perspective, as supported by Hassan et al. (2023) using textual analysis[3], although our model, measures, and empirical analysis do not rely on the types of shocks. However, multiple sources of evidence suggest that demand shock is more likely to be the dominant force in the case of the SARS shock, because the inventories of both output and intermediate inputs increased and PPI decreased during SARS. Moreover, the markup and PPI declined by almost the same magnitude, suggesting no significant changes in marginal production costs.

The paper is related to three strands of literature, besides the one on markup measurement. The first strand is the literature on the impact and determinants of market power. Market power plays a vital role in various fields of economics, by influencing social welfare, resource allocation, and economic development (e.g., De Loecker et al., 2020; Autor et al., 2020; De Loecker and Warzynski, 2012; Hsieh and Klenow, 2009; Syverson, 2019; Edmond et al., 2023). It is costly for firms to establish market power; it is also costly for regulators to limit the market power of large firms (e.g., Bork, 1978; Posner, 1970; Peltzman, 2014). This paper shows that large economic shocks, such as epidemics, provide an opportunity to redistribute market power across firms, which may have a long-term impact on the market structure.

Second, it relates to the literature on how natural disasters and epidemics influence economic activities (e.g., Young, 2005; Barrot and Sauvagnat, 2016). SARS may influence firms' global input sourcing (Huang, 2019) and generate long-lasting effect on firms' trade growth (Fernandes and Tang, 2020). Cavallo et al. (2014) find that the earthquakes in Japan and Chile had larger impacts on the available variety of products than output prices in the supermarket industry. We contribute by providing empirical evidence on the impact of the SARS epidemic on markup. More importantly, we identify a novel channel of inventory and demand uncertainty, which contributes substantially to the decline in markup after the shock.

The paper also contributes to the literature on the cyclicality of markup during business cycles. Markups are found to be countercyclical due to reasons such as sticky price and

[3] They use textual analysis and find that COVID-19 brought equally important shocks to firms' demand and supply, while during Ebola, SARS, H1N1, Zika, and MERS, firms were more focused on demand shocks.

procyclical marginal cost (Bils, 1987; Rotemberg and Woodford, 1999), financial constraints (Chevalier and Scharfstein, 1995, 1996; Amountzias, 2021), or endogenous procyclical business formation (Jaimovich and Floetotto, 2008). Kryvtsov and Midrigan (2012) further find that markups are countercyclical following monetary-driven business shocks. In contrast, Domowitz et al. (1986) find that markup is procyclical facing demand shocks because given short-run capacity constraints, increases in demand may lead to price increases that raise markup. In line with Domowitz et al. (1986), we show that markup is procyclical facing the negative SARS shock which reduces prices and increases inventory costs.

Section 2 describes the background and motivational facts. Section 3 develops the model. Section 4 discusses the measurement and tests the model predictions. Section 5 reports the main results. Section 6 provides further causal evidence. Section 7 discusses the heterogeneity of the SARS impacts, followed by robustness checks in Section 8. Section 9 concludes.

2 Background, Data, and Motivational Facts

2.1 The 2003 SARS Epidemic Shock in China

The SARS epidemic first emerged in China in late 2002 in Guangdong province, and then it spread in 2003 to other provinces in China, as well as 29 countries on five continents globally. It led to a worldwide health threat (Heymann et al., 2013), especially in China. More than 8,000 people were infected and 774 died. The majority of the infections were within Mainland China, which accounted for 87.5% of all infected cases and 80% of all deaths in the world. Within Mainland China, four provinces (Guangdong, Beijing, Shanxi, and Inner Mongolia) were hit hardest, accounting for 90% of all infected cases and 87% of all deaths in Mainland China. SARS ended in the third quarter of 2003 for most provinces in China. Figure A4 in Appendx F shows the distribution of infected cases across the provinces.

SARS created a large shock to production, consumption, and investment in China, especially in the heavily hit provinces. Compared with the ongoing COVID-19 pandemic, although SARS caused fewer infections and deaths, it had a much higher fatality rate, at 9.2%. The fear among consumers, firms, and investors and the high uncertainty about future trends led to a large negative shock to the Chinese economy, especially in the heavily hit provinces. The strict government policies to lock down some economic activities further enlarged the impact of the shock. This may generate a large impact on firms in the affected areas.

2.2 Data and Motivational Facts

The analysis uses a detailed firm-level data set, the Annual Survey of Industrial Enterprises, collected by the National Bureau of Statistics of China from 1998 to 2007. The data set includes all Chinese state-owned enterprises (SOEs) and non-SOEs whose annual sales are no less than RMB 5 million. Detailed production information is reported in the data set, including the values of output, sales, and end-of-period inventory stock and the variable costs the firm expended in production. Data on the SARS epidemic were released by World Health Organization (WHO), which reports the timing and number of infected cases and death in different provinces in China. The data on prefecture-level characteristics (such as gross domestic product (GDP) per capita and population density) are from the CEIC Global Database, which provides comprehensive macroeconomic data for more than 200 economies.[4]

We first show preliminary evidence on the impact of SARS on the market share, markup, and inventory of SARS-affected firms, relative to others. Figure 1(a) plots the evolution of the total market share of the four SARS-affected provinces, defined as the total share of sales of firms in the four provinces relative to national sales.[5] While the market share of the treated provinces was increasing before the outbreak of SARS in 2003, it experienced a continued decline after that. Consistently, their market power declined after the SARS shock relative to firms in other provinces, as shown in Figure 1(b). Here market power is proxied by the firm's *raw markup*, which is defined as the ratio of the firm's output value ($Routput_{j,t}$)

[4]Data for Chinese prefecture-level cities' characteristics are available with a valid license on the CEIC Global Database website: `http://insights.ceicdata.com/`.

[5]Because four provinces (Beijing, Guangdong, Shanxi, and Inner Mongolia) were hit hardest and accounted for 90% of all cases of infection in China, we treat firms located in these four provinces as the treatment group and firms located in other provinces as the control group in our main specification.

produced in one period to the corresponding variable production costs ($TVC_{j,t}$), as follows:

$$\tilde{\mu}_{j,t} = \frac{Routput_{j,t}}{TVC_{j,t}}. \tag{1}$$

We emphasize that output value, instead of sales, should be used in the definition of raw markup in contrast to sales typically used in the literature (see De Loecker and Warzynski, 2012; Brandt et al., 2017; Foster et al., 2008; De Loecker et al., 2016, among others), because it is the output rather than sales that corresponds to the current period production costs. In Section 4.1, we discuss the validity of this measure and how it is linked to the (raw) markup estimated using the production approach (e.g., De Loecker, 2011; De Loecker and Warzynski, 2012; Raval, 2023). These facts imply that SARS may have re-distributed the market share and market power from firms in the treated provinces to those in the control provinces.

Figure 1(c) and 1(d) shows that before SARS, the treated and control groups of firms experienced a similar decreasing trend in the average inventory level and inventory ratio.[6] However, both measures of inventory of the treated provinces declined substantially after the shock, presumably due to the negative demand shock that resulted from SARS. The effect is long-lasting. To sum up, the raw data patterns provide preliminary evidence on the impact of the SARS shock on the redistribution of market power and firms' inventory holding.

3 A Model of Inventory and Market Power

This section develops a dynamic model of firms' production and pricing to show how uncertain demand and inventory influence market power, by extending Kahn (1987) to allow for flexible markup. The model implies a new measure of market power (markup) when firms endogenously choose inventory, pricing, and production dynamically facing demand uncertainty.

[6]The inventory ratio is defined as the ratio of the end-of-year (EOY) inventories to the total amount of products available for sale in each period, $Inventory\ Ratio_{j,t} = \frac{Rinventory_{j,t}}{Rinventory_{j,t-1}+Routput_{j,t}}$. Here $Rinventory_{j,t}$ is EOY inventory and the total amount of products available for sale at t, $Rinventory_{j,t-1} + Routput_{j,t}$, equals the sum of the beginning-of-year (BOY) inventory and output produced during this period.

3.1 Model Setup

Firms produce a single output and compete monopolistically in the output market.[7] At the beginning of period t, each firm observes its state, including last period ending inventory n_{t-1}, current firm-level characteristics Γ_t (capital stock, size, age, etc.), and macro-level demand status. It pays the inventory costs for holding n_{t-1}[8] and then chooses the output y_t and price p_t to maximize the expected long-term discounted profits. The realized EOY inventory, n_t, is stochastic due to the demand uncertainty. To save notation, we omit the firm subscript, firm characteristics, and macro variables in this section.

The demand function faced by individual firms in period t is stochastic, as follows:

$$x_t = h(p_t) + u_t, \tag{2}$$

where $h(p_t)$ is a deterministic function of price p_t, and u_t is the unexpected demand shock that is serially uncorrelated, independently and identically distributed (i.i.d.) with mean zero and variance σ_u^2.[9] Denote $G(\cdot)$ as the cumulative distribution function of u_t and $g(\cdot)$ as the corresponding probability density function.

Given any BOY inventory n_{t-1}, current year output y_t, and price p_t, the actual sales are the minimum of the available output $n_{t-1} + y_t$ and demand x_t,

$$z_t = \min(n_{t-1} + y_t, x_t). \tag{3}$$

Equation (3) demonstrates the difference between sales and demand caused by the existence of uncertain demand and inventory dynamics. Given (n_{t-1}, y_t, p_t), a high demand shock

[7] As a caveat, the single-product assumption rules out the possibility for firms to adjust product composition. Moreover, as an anonymous referee pointed out, although our model assumes monopolistic competition, our empirical analysis is more general and is consistent with a broader range of models.

[8] It does not matter whether the firm pays the inventory costs for holding n_{t-1} at the beginning of year t or at the end of $t-1$. They yield the same prediction of the markup and inventory dynamics in our model.

[9] Note that our markup measure, as defined in (10), is more general and it does not depend on the assumptions of i.i.d. and serially uncorrelated demand shocks.

will drain the total products available for sale, leading to stocking out. In contrast, a low demand shock reduces the actual demand, generating high inventory at the end of t. Define $Q_t \equiv n_{t-1} + y_t - E_t(x_t) = n_{t-1} + y_t - h(p_t)$ as the difference between the total goods available for sale and expected demand. Then Q_t also represents the (expected) target of EOY inventories. Stockout happens if and only if the demand shock is greater than the expected target inventories $u_t > Q_t$. So the stockout probability is $\Pr(u_t > Q_t) = 1 - G(Q_t)$, where $G(Q_t) = \int_{-\infty}^{Q_t} g(u_t)\, du_t$. For given (n_{t-1}, y_t, p_t), it is straightforward to show that the expected sales are: $E_t(z_t) = \int_{-\infty}^{Q_t} [h(p_t) + u_t]\, dG(u_t) + \int_{Q_t}^{\infty} (n_{t-1} + y_t)\, dG(u_t)$. No matter whether stockout happens or not, the following accounting equation always holds:

$$n_{t-1} + y_t = z_t + n_t. \tag{4}$$

That is, the total amount of products available for sale at the beginning equals the sum of sales and resulting EOY inventory. It also defines the realization of the stochastic inventory.

The usual production costs as $C_Y(y_t)$ contain direct expenditures to produce products, such as material expenditure, labor wages, etc. The firm in addition pays an inventory cost $C_N(n_{t-1})$ if it carries some inventories over periods. Examples of inventory costs include warehouse costs, inventory management costs, etc. Assume the two cost functions are increasing and convex satisfying the conditions: $C'_Y(\cdot) > 0, C''_Y(\cdot) \geq 0; C'_N(\cdot) > 0, C''_N(\cdot) \geq 0$.

3.2 Optimal Production, Pricing, and Inventory Dynamics

Observing its BOY inventories, the firm chooses price p_t and output y_t to maximize the discounted expected profits, $E_t \left\{\sum_{s=t}^{\infty} \beta^{s-t}[p_s z_s - C_Y(y_s) - C_N(n_{s-1})]\right\}$. The optimal decisions can be characterized in the following dynamic programming problem in recursive form:

$$\begin{aligned} V(n_{t-1}) = \max_{y_t, p_t} \quad & E_t \left\{p_t z_t - C_Y(y_t) - C_N(n_{t-1}) + \beta V(n_t)\right\}, \\ \text{subject to:} \quad & (2),\ (3),\ \text{and } (4). \end{aligned} \tag{5}$$

The first-order condition with respect to the optimal production and pricing decisions are[10]

$$p_t\left[1-G(Q_t)\right]+\beta\int_{-\infty}^{Q_t}V'(n_t)\,dG(u_t)=C'_Y(y_t). \tag{6}$$

$$E_t(z_t)+\frac{\partial E_t(z_t)}{\partial p_t}p_t=\frac{\partial h(p_t)}{\partial p_t}\beta\int_{-\infty}^{Q_t}V'(n_t)\,dG(u_t). \tag{7}$$

Given output prices, the choice of output level ensures that the expected payoff equals the marginal cost of production. As a key feature, the firm must weigh the possibility of stockout against the possibility of holding too much inventory when choosing output, due to demand uncertainty. If the firm produces more, it reduces the stockout probability and increases the expected payoff from the current period, but it also increases inventory and inventory costs.

The optimal production condition clarifies an important insight: the true economic cost of producing one more unit of product includes not only the usual marginal cost of production $C'_Y(y_t)$, but also the cost of holding potentially more inventory and the benefit of reducing the possibility of stockout. This insight has an important implication for the empirical measurement of market power: it requires knowledge of the marginal economic costs of supplying one more unit of output, inclusive of the marginal cost of production, expected inventory costs, and the impact on the stockout probability.

The first-order condition for pricing, (7), ensures that the marginal benefit of increasing price derived from period t equals the value of carrying the unsold product (due to increased price) as inventory to next period. Inventory costs influence firms' decisions by affecting the marginal value of holding more inventory, $V'(n_t)$, as seen from the Euler equation as follows:

$$V'(n_{t-1})=-C'_N(n_{t-1})+\beta\int_{-\infty}^{Q_t}V'(n_t)\,dG(u_t). \tag{8}$$

Given the downward-sloping demand function and the assumptions on the production and inventory cost, the optimization problem admits a unique solution. The first-order conditions,

[10]Please refer to Appendix A.2 and A.3 for detailed derivations of (6), (7), and (8).

(6) and (7), and Euler equation (8) together determine the firm's optimal price and output as functions of BOY inventory and demand uncertainty: $y_t = y_t(n_{t-1}, \sigma_u)$ and $p_t = p_t(n_{t-1}, \sigma_u)$. Then the distribution of the actual EOY inventory, n_t, is determined from (4).

3.3 Measuring Market Power

Following the macro literature with inventory dynamics (e.g., Kryvtsov and Midrigan, 2012; Yu, 2019), we define the markup as $\mu_t = \frac{\varepsilon_t}{1+\varepsilon_t}$. Here the elasticity of expected sales [11], $\varepsilon_t \equiv \frac{\partial E_t(z_t)}{\partial p_t}\frac{p_t}{E_t(z_t)} = e_t \cdot \frac{h(p_t)G(Q_t)}{E_t(z_t)}$, is proportional to the elasticity of the original demand function ($e_t \equiv \frac{\partial h(p_t)}{\partial p_t}\frac{p_t}{h(p_t)}$), adjusted by the impact of the stockout probability as captured by the ratio of expected sales in the case of not-stockout to total expected sales, $\frac{h(p_t)G(Q_t)}{E_t(z_t)}$. The intuition for this adjustment is as follows. With possibility $G(Q_t)$ of not stocking out, the expected sales elasticity is equivalent to e_t; with possibility $1 - G(Q_t)$ when stockout occurs, the effect of a price change on sales is zero. So ε_t captures the effective impact of a price change on expected actual sales, taking into account the effect of stockout. Because the effective demand is less elastic than the original demand as $0 < \frac{h(p_t)G(Q_t)}{E_t(z_t)} < 1$, the corrected markup is higher than the conventional markup, $\frac{e_t}{1+e_t}$. (7) implies the following markup:

$$\mu_t \equiv \frac{\varepsilon_t}{1+\varepsilon_t} = \frac{p_t}{\frac{\beta\int_{-\infty}^{Q_t} V'(n_t)\, dG(u_t)}{G(Q_t)}}. \tag{9}$$

$\frac{\beta\int_{-\infty}^{Q_t} V'(n_t)\, dG(u_t)}{G(Q_t)}$ is the value of carrying one unit of inventory to next period conditional on not stocking out. At the optimum, it equals the net costs of supplying this unit, taking into account the production costs, inventory costs, and stockout probability. So (9) says markup equals the ratio of price over total variable costs of supplying one more unit of inventory.

Because the optimal pricing and production decisions depend on the BOY inventory and the level of demand uncertainty, so does markup. The following conjecture summarizes the potential impact of the BOY inventory and demand uncertainty on endogenous market power,

[11] Please refer to Appendix A.1 for detailed derivations.

when firms optimally choose prices and production to maximize the long-term payoff.

Conjecture 1 *A firm's market power decreases in its BOY inventory stock and demand uncertainty, other things being equal.*

To understand the intuition behind the effect of BOY inventory on market power, first consider a special case with constant marginal production costs and zero inventory costs. In this case, the optimal markup μ_t, price p_t, and not-stockout probability $G(Q_t)$ are constant, as predicted in Kahn (1987). This is because adjusting current production is cost-free, so the firm fully adjusts its production to make up for the unexpected changes in BOY inventory, while keeping prices and $G(Q_t)$ unchanged. With increasing marginal production costs and inventory costs as in our model, however, adjusting output is no longer cost-free. When facing an unexpected increase in BOY inventory, the firm will have an incentive not to adjust the production level fully to compensate for the unexpected changes in BOY inventory. Instead, it has an incentive to lower the price to sell (some) of the extra inventory stock, leading to a decrease in the markup. The conjecture that markup decreases in the firm's BOY inventory is consistent with the predictions of many alternative inventory models, such as Zabel (1970) in a similar but static model, Aguirregabiria (1999) in a classic (S, s) model, and Kryvtsov and Midrigan (2012) in a standard New Keynesian model with price and wage rigidity.

The conjecture on the negative effect of demand uncertainty on markup is also intuitive. When demand uncertainty increases, the probability of stockout increases if the targeted inventory remains unchanged. This leads to a loss of expected revenue in the current period due to stockout. To reduce such losses, the firm has an incentive to produce more and hold more inventory to reduce stockout probability, as long as the cost of increasing output is not too large relative to that of increasing prices to reach the higher inventory target. This increases the inventory costs and production costs due to increasing marginal costs, leading to a lower markup. This conjecture is consistent with the findings of Carlton and Dana (2008), who prove that firms will respond to a higher degree of demand uncertainty by reducing the markup through quality choice in a static model. These conjectures are empirically tested in

Section 4, using a panel of Chinese manufacturing firms from 1998 to 2007.

3.4 Extension: Serially Correlated Demand Shifter

To fix the idea, our model above assumes i.i.d. demand shifter. However, demand shifter could be serially correlated. Assume that the demand function is $x_t = \widetilde{h}(p_t) + \phi_t$, and the demand shifter (ϕ_t) follows an AR(1) process, $\phi_t = \rho_0 + \rho_1\phi_{t-1} + u_t$. Here u_t is the innovation to demand shifter and is i.i.d. The demand function allows for serially correlated demand shifter and can be rewritten as $x_t = h(p_t, \phi_{t-1}) + u_t$. It is straightforward to show that all analysis in Section 3 and the markup measures in Section 4 still apply by replacing $h(p_t)$ by $h(p_t, \phi_{t-1})$. So is the empirical analysis.

The serially correlated demand may contribute to the long-lasting effects of a temporary demand shock. In Appendix D, we simulate the extended model and show that a temporary demand shock can generate long-lasting effects on market power through the mechanisms of serially correlated demand shifter and increased demand uncertainty, as in Conjecture 1.

4 Empirical Measurement and Correlation

This section constructs the key measures used in our empirical analysis and empirically tests the negative relationships between inventory/demand uncertainty and markup in the data.

4.1 Empirical Measure of Market Power

In the definition of markup in (9), $p_t / \left[\frac{\beta \int_{-\infty}^{Q_t} V'(n_t)\, dG(u_t)}{G(Q_t)}\right]$ is not readily measurable from data. To address this problem, we replace $\beta \int_{-\infty}^{Q_t} V'(n_t)\, dG(u_t) = C'_Y(y_t) - p_t\,[1 - G(Q_t)]$ in (6) into the definition of markup in (9), yielding the markup:

$$\mu_t \quad = \quad \frac{\varepsilon_t}{1+\varepsilon_t} = \frac{p_t G(Q_t)}{C'_Y(y_t) - p_t[1-G(Q_t)]} = \frac{\tilde{\mu}_t G(Q_t)}{1-\tilde{\mu}_t[1-G(Q_t)]}. \tag{10}$$

where the raw markup $\tilde{\mu}_t = p_t/C'_Y(y_t)$ is the ratio of price to marginal cost of production. This equation provides an intuitive alternative way of interpreting and measuring markup from the supply side. $p_t G(Q_t)$ is the (unconditional) expected revenue the firm can earn from selling one unit of product. $C'_Y(y_t) - p_t[1 - G(Q_t)]$ is the total economic costs of producing one more unit of product, which includes the marginal cost of production and the net benefit of reducing the stockout probability when holding more inventory. So markup is the ratio of the unconditional price to the total marginal costs of supplying the output. In the special case when there is no demand uncertainty or inventory problem, $G(Q_t) \equiv 1$ for all Q_t and the markup in (10) degenerates to the raw markup $\tilde{\mu}_t$, as widely used in the literature.

Equation (10) provides a straightforward method to calculate the markup empirically: first, calculate the raw markup $\tilde{\mu}_t$, by using data or estimation; then, estimate the not-stockout probability $G(Q_t)$ from inventory data and use it to adjust the markup following (10). One attractive advantage of this measure is that although inventory cost affects markup, they do not appear in (10) because its impact is absorbed in the endogenous not-stockout probability $G(Q_t)$ and raw markup μ_t. As a result, data on inventory costs—usually not recorded separately in most production data sets—are not needed to calculate markup empirically. This broadens the applicability of this method. In the following, we show how to construct the probability of not stocking out $(G(Q_t))$ and the raw markup $(\tilde{\mu}_t)$ in detail.

Not-stockout probability ($G(Q_{jt})$). To match the panel feature in the application, we allow all the firm-specific variables, $(\mu_{jt}, \tilde{\mu}_{jt}, Q_{jt})$, to vary across firms ($j$) and over time ($t$). We also add firm-time specific characteristics, Γ_{jt}, to allow for more firm heterogeneity.

We use the probit model to estimate the probability of not stocking out, $G(Q_{jt})$, from the observed data on whether a firm stocks out or not. As implied by the model, the probability of not stocking out ($\chi_{j,t} = 1$) is

$$\begin{aligned}\Pr\{\chi_{j,t} = 1|\Gamma_{jt}\} &= G(Q_{jt}|\Gamma_{jt}) = \Pr(u_{jt} < Q_{jt}|\Gamma_{jt}) = \Pr(u_{jt} < n_{jt-1} + y_{jt} - h(p_{jt})|\Gamma_{jt}) \\ &= \tilde{G}(n_{jt-1}, y_{jt}, p_{jt}, \Gamma_{jt}) = \tilde{G}(n_{jt-1}, \Gamma_{jt}). \qquad (11)\end{aligned}$$

The third equality holds due to the definition of Q_{jt}. The fourth equality is a re-writing of the probability function. The last equality holds because the endogenous output and prices, (y_{jt}, p_{jt}), are functions of (n_{jt-1}, Γ_{jt}) as implied by the model. We also control for time fixed effects, 4-digit industry fixed effects, and city fixed effects in the estimation. We estimate (11) industry by industry (2-digit) and obtain estimates of the probability of not stocking out, $\tilde{G}_{jt}$. Overall, the model can predict the stockout status in the data at a success rate of 76%. To save space, we only report the estimation results by pooling all industries together in Table A2 in Appendix F. Industry-level estimation results are available upon request.

Raw markup ($\tilde{\mu}_{jt}$). The second component for constructing the new markup measure in (10) is the raw markup, which is defined as the ratio of output prices to marginal production costs ($\tilde{\mu}_{jt} \equiv p_{jt}/C'_{Y\,jt}$). Interestingly, the production function approach (e.g., De Loecker, 2011; De Loecker and Warzynski, 2012), with a slight modification,[12] can still be used to estimate the raw markup ($\tilde{\mu}_{jt}$) consistently if output quantity data are available, because it only relies on the static cost minimization assumption. Then, given $\tilde{\mu}_{jt}$, together with $G(Q_{jt})$ estimated above, we can calculate the final markup μ_{jt} using (10).

However, because output quantity is not available in our data, as in many other datasets, we are not able to use the production function approach directly to estimate the raw markup (Bond et al., 2021). Instead, we choose to calculate the raw markup directly from the data in the main application to avoid any specification and estimation errors. Specifically, in the main results we calculate the raw markup as the ratio of output value produced in this period to the associated variable production costs, which include expenditures on labor and materials, as defined in (1) in section 2.2. We check the robustness when using alternative measures of raw markup as follows.

This measure is a concept of average raw markup. Although it places some restrictions on the shape of the production function to be consistent with the usual measure of (marginal) raw markup, it saves us from any estimation errors from using production or demand approaches.

[12] When estimating the output elasticity of flexible inputs, we have to control for the BOY inventory in the control function of productivity to account for the impact of inventory heterogeneity on input choices.

It is an accurate measure of the usual marginal raw markup if the sum of the output elasticities of all the variable inputs equals one (constant variable returns to scale). When the variable returns to scale is not one but is a constant, the measured markup will be biased by a factor of the returns to scale. In this case, our difference-in-differences style estimate is still qualitatively consistent, although quantitatively there may be bias. However, the difference-in-differences estimate based on logarithm markup is still consistent, because the scale term will be cancelled. Hence, we also report the results based on logarithm markup.[13]

Given the measure of raw markup, $\tilde{\mu}_{jt}$, and the adjustment term, $G(Q_{jt})$, we then can calculate the correct measure of market power in the presence of demand uncertainty and endogenous inventory heterogeneity, following (10).

Alternative Measures of Markup. We test the robustness of the results using four alternative measures of markup. First, we use the costs of goods sold to represent variable production costs to include variable costs that arise from capital usage and other inputs. We define a new raw markup as the ratio of total sales to the costs of goods sold. Then the markup measure is obtained from (10) similarly as before.

Second, we obtain an approximation of user costs of capital stock, include the capital costs in variable production costs, and calculate a measure of markup that is similar to that defined in Raval (2023). In this case, capital is treated as a fully variable input. Following the literature (e.g., De Loecker et al., 2020; De Loecker and Eeckhout, 2021; Raval, 2023), the rental rate of capital is the sum of the real interest rate and the depreciation rate: $r_t = I_t - \Pi_t + \Delta$, where I_t is the nominal interest rate, Π_t is the inflation rate, and Δ represents the average depreciation rate.[14] A firm's user costs of capital are measured by its current value of capital stock multiplied by the rental rate. We define a new raw markup as the ratio of the value of output to the sum of expenditures on intermediate inputs, labor wages, and user costs of capital stock. Then the second markup measure is obtained by

[13] We appreciate an anonymous referee for pointing this out and suggesting this check.

[14] The data for real interest rates were obtained from the World Bank World Development Indicators. The depreciation rate is calculated based on the annual depreciation value reported in the data set to calculate the average ratio of annual depreciation value to current capital stock, which we use as the depreciation rate.

adjusting the new raw markup for inventory and demand uncertainty based on (10).

Third, we use the raw markup, as defined in (1). This is to show that our results are not merely driven by how we adjust the markup for inventory and demand uncertainty. Instead, if the basic results still hold for the raw markup, it indicates that the pricing and/or production costs are also affected by the SARS shock.

The fourth measure is based on the insight of De Loecker and Warzynski (2012). As discussed, the production approach (e.g., De Loecker, 2011; De Loecker and Warzynski, 2012) can still provide a consistent estimate of the raw markup in the presence of demand uncertainty and inventory heterogeneity, if output quantity is available in the data. However, although the input share is readily available in the data, the lack of output quantity data prevents us from consistently estimating the output elasticity as suggested in Bond et al. (2021). To address this problem, we replace the output elasticity of material by the average material share in total variable costs, which is valid under some conditions. Then the raw markup is constructed by using the insight of Hall (1988) and De Loecker and Warzynski (2012). The the markup can be constructed based on (10) as before.

4.2 Empirical Measure of Demand Uncertainty

We measure demand uncertainty as the standard deviation of the unexpected demand shocks a firm faces. We construct the unexpected demand shocks following the insight of Kumar and Zhang (2018). They show that the firm's deviation of inventory share from the target inventory captures important information on unexpected demand shocks in a stockout-avoidance model based on Kahn (1987). The same idea applies in our context. We can estimate the unexpected demand shocks as the residual of the following estimation equation:

$$Inventory\ Ratio_{j,t} = f(\Gamma_{jt}) + \lambda_{city} + \lambda_{ind} + \lambda_t + u_{j,t}, \tag{12}$$

where Γ_{jt} are firm characteristics including firm size, age, and ownership; λ_{city} are the fixed effects of the city in which the firm is located; λ_{ind} are the 4-digit industry fixed effects; and λ_t represent the time fixed effects. We regress the above equation industry by industry (2-digit Standard Industrial Classification (SIC) level) and use the predicted residuals $\hat{u}_{j,t}$ as a measure of firm-level unexpected demand shocks. Controlling the time fixed effects implies that the firm can predict the average time trend of unexpected demand shocks.

We assume that firms in the same city and the same industry (2-digit SIC level) face common demand uncertainty at each given time. Then the demand uncertainty faced by each firm can be calculated as the standard deviation of the unexpected demand shocks of firms in the same city and industry as $Demand\ Uncertainty_{j,t} = \sigma_{city,ind,t}(\hat{u}_{j,t})$.

Table A3 shows the summary statistics for the key variables. While the raw markup and adjusted markup show high correlation, the level of adjusted markup is higher than the raw markup. This is consistent with the theoretical prediction as discussed in Section 3.

4.3 Correlation between BOY-Inventory and Market Power

We estimate the following equation to test the conjectured relationship between inventory stock, demand uncertainty, and markup:

$$\mu_{j,t} = \beta_0 + \beta_1 InventoryRatio_{j,t-1} + \beta_2 DemandUncertainty_{j,t} + \beta_\Gamma \Gamma_{j,t} + \lambda_j + \lambda_t + \epsilon_{j,t}. \quad (13)$$

β_1 and β_2 measure the association of the BOY inventory ratio and demand uncertainty with markup, respectively. $\Gamma_{j,t}$ controls for firm characteristics, including capital stock and export status. λ_j and λ_t control for firm and time fixed effects, respectively. The difference in the observations between Table A3 and columns (1) and (3) in Table 1 arises from the fact that creating the lagged term for the inventory ratio results in losing one year of observations.

The estimation results strongly support the model conjectures. As reported in Table 1, markup decreases in the firm's BOY inventory stock and demand uncertainty, conditional on other state variables. An increase of 1% in the BOY inventory ratio is associated with a decrease of 0.202% in the markup, and an increase of 1% in demand uncertainty is associated with a decrease of 0.213% in the markup. Economically, this impact is substantial. It implies that a one standard deviation increase in the BOY inventory ratio (demand uncertainty) is associated with a 2.4 (0.6) percentage points decline in the markup. When using the logarithm markup, as one anonymous referee suggested, we find consistent results. One caveat is that the results in Table 1 are correlations, not necessarily causal relationships, due to potential reverse causality and endogeneity.

5 Main Estimation Results

Specification. This section examines the impact of the SARS epidemic on the redistribution of market power and the role played by inventory stock and demand uncertainty. Because SARS generated a large negative shock to firms located in provinces that were seriously affected but much less of a shock to firms in other provinces, it provides a natural experiment to analyze the impact of epidemics on market power using a difference-in-differences style analysis. In our analysis we treat firms located in the four heavily-hit provinces (Beijing, Guangdong, Shanxi, and Inner Mongolia) as the treatment group and those located in other provinces in Mainland China as the control group. Then the difference between the two groups capture the redistribution of market power across firms when markup is used as the dependent variable. Specifically, we estimate the following baseline regression function:

$$Y_{j,t} = \beta_0 + \beta_{treated*SARS}(Treated_j * SARS_{j,t}) + \beta_\Gamma \Gamma_{j,t} + \beta_z Z_{city,t} + \lambda_{city} + \lambda_{ind} + \lambda_t + \epsilon_{j,t}, \quad (14)$$

where the dependent variable refers to markup, inventory ratio, or demand uncertainty. The dummy variable $Treated_j$ equals 1 if firm j is in one of the four provinces that were heavily hit by SARS and 0 otherwise. The dummy variable $SARS_{j,t}$ controls the timing of the SARS shock. Because Guangdong was the first province that experienced the SARS epidemic in the fourth quarter of 2002, while in other affected provinces SARS outbreaks began in the first quarter of 2003, $SARS_{j,t}$ equals 1 for firms in Guangdong from 2002 and onward and for firms in all other provinces from 2003 and onward. $SARS_{j,t}$ equals zero otherwise.[15] $\Gamma_{j,t}$ represents the firm-level, time-varying characteristics, which include the capital stock and export status. $Z_{city,t}$ represents the city-level, time-varying characteristics, including city-level GDP per capita, city-level population density, and city-level export share (value ratio of total exports to total outputs), which is included to control the potentially effects of China's entering the World Trade Organization (WTO) on different provinces during our study period. We also control for 4-digit industry fixed effects λ_{ind}, year fixed effects λ_t, and city fixed effects λ_{city}. The key parameter of interest, $\beta_{treated*SARS}$, measures the impact of the SARS epidemic on the distribution of market power between the SARS-affected firms and un-affected firms.

To investigate the dynamic effects of the SARS epidemic and test for any potential pre-trend, we estimate an extended version of (14) by allowing SARS to have a flexible yearly effect. Specifically, we consider a full set of interactions between the treated dummy and year dummies over our study period and estimate the following equation:

$$Y_{j,t} = \beta_0 + \sum_{t=1999}^{2007} \beta_{treated*t}(Treated_j * D_t) + \beta_\Gamma \Gamma_{j,t} + \beta_z Z_{city,t} + \lambda_{city} + \lambda_{ind} + \lambda_t + \epsilon_{j,t}, \quad (15)$$

where D_t is the year dummy and $\beta_{treated*t}$ represent the differential performance of firms in affected provinces relative to firms in unaffected provinces in year t. All other variables and parameters are the same as previously defined in (14).

Pre-trend test and correction. The markup of firms in SARS-affected areas had a growing trend compared with firms in the control group before the outbreak of SARS, as shown in Appendix Figure 1.[16] The upward pre-trend, if ignored, will underestimate the true impact of SARS on markup. A further analysis shows that the pre-trend in markup was

[15] In the robustness check in Section 8, we show that our results are similar when using uniform cutoffs. That is, $SARS_t = 1$ for any firm j from 2003 and onward and zero otherwise, regardless of the province.

[16] We test the null hypothesis that SARS-affected firms and unaffected firms had a common trend in markup before the shock. The F-test statistic is 12.47 with a p-value of 0.000, rejecting the null hypothesis.

completely driven by Guangdong province, which had faster growth of markup relative to the control group, as shown in Figure A5. This was probably driven by Guangdong's fast industrial upgrading and heavy investment in research and development throughout our data period. In the other three heavily hit provinces (Beijing, Shanxi, and Inner Mongolia), there was no significant differential pre-trend in markup compared with the control group.

To address this potential problem, we detrend markup, inventory ratio, and demand uncertainty in two steps following Rambachan and Roth (2023). In the first step, we estimate the differential pre-trend of markup, inventory ratio, and demand uncertainty for firms in Guangdong, Beijing, Shanxi, Inner Mongolia, and the control provinces, using data before the SARS outbreak. Specifically, we estimate a regression function of dependent variables by including five interaction terms of time trend with dummies representing Beijing, Guangdong, Shanxi, Inner Mongolia, and the control provinces, after controlling for the same control variables and fixed effects as in (14). In the second step, we construct the detrended dependent variables for the treated and control provinces by subtracting the original dependent variables from their pre-trend estimates for all years. This treatment removes the differential pre-trend in the dependent variables between firms in the treated and control provinces, under the assumption that the differential pre-trend before the SARS shock would be maintained after the shock. We use the detrended dependent variables in the analysis throughout the paper.[17]

5.1 SARS and the Redistribution of Market Power

Figure 2 compares the distribution of markup in the treatment group (Beijing, Guangdong, Shanxi, and Inner Mongolia) and the control group (other provinces) in 2001 and 2005. Right before the SARS outbreak (2001), all the firms in the treatment and control groups show

[17] The estimation results without detrending markup are robust qualitatively, although the estimates are slightly lower as expected. The results are available upon request. The pre-trend for inventory and demand uncertainty in the original data is statistically insignificant. The statistics of the F-test show that the null hypothesis of common trend cannot be rejected before the shock, with the F-test statistics being 1.02 with a p-value of 0.340 for inventory and 0.35 with a p-value of 0.703 for demand uncertainty, respectively. So detrending has almost no impact on the estimation results for the impact of SARS on inventory and demand uncertainty. The results without detrending inventory and demand uncertainty are available upon request.

similar distributions of markup. However, in 2005 after the SARS shock, the distribution of markup of the treated group shifted left, while that of the control group only experienced a very mild increase. This result provides preliminary evidence that the SARS shock may have re-distributed market power between SARS-affected firms and non-affected firms.

Table 2 reports the estimation results of the impact of SARS on firm markup for the baseline specification (14). In the baseline result in column (1), the SARS epidemic substantially reduced the markup of firms located in SARS-affected provinces by 7.8 percentage points on average, relative to firms located in other provinces. Columns (2) and (3) in addition control for the firm's capital stock, firm-level export status, and city-level export share, to remove firm size effects and heterogeneous impacts of entering the WTO on different firms and provinces. The results are robust. These results support that SARS, as a large negative shock to firms in the affected areas, may have increased firms' costs or forced firms to reduce output prices, resulting in reduced market power relative to unaffected firms.

Figure 3(a) reports the dynamic effects of SARS on market power based on (15), with the point estimates and corresponding 95 percent confidence intervals. The year 2002 is chosen as the base year. Several observations stand out. First, the markup of SARS-affected firms decreased substantially by over 5.5 percentage points relative to other firms in 2003, right after the outbreak of SARS, while their markup was relatively stable before SARS.

Second, the effect of SARS on the redistribution of market power is long-lasting. After the initial large drop in 2003, the markup of firms located in the SARS-hit areas continued to decline relatively to an accumulated reduction of 13.8 percentage points by 2007. This dynamic effect demonstrates that although the epidemic is typically regarded as a temporary shock, it had a long-lasting effect on firm performance. This finding is in line with Fernandes and Tang (2020), who also find that the SARS effect is long-lasting. This suggests that market power is quite persistent and, once established, it is not easy to change. It also suggests that some fundamental factors that affect firm markup may have changed due to the SARS shock, as discussed in Sections 5.2 and 8.

As discussed in Section 4.1, the main results based on level markup is consistent when there is constant variable returns to scale. However, the result may be biased if variable returns to scale is not 1. In this case, the difference-in-differences analysis based on the logarithm of markup is still consistent, because the variable returns to scale will drop out as long as the SARS shock does not affect production technology. The results are reported in Columns 4-6 in Table 2. The estimates using logarithm are qualitatively and quantitatively consistent with our main results. In the table, SARS reduced the markup of treated firms relatively by *5.7%*. Given the mean markup of 1.291 in the data, it means SARS increases the markup of treated firms relatively by 7.4 percentage points, which is very close to our main results (7.8 percentage points) using markup level as reported in Table 3. Moreover, the pretrend test and dynamic effects using the logarithm markup are also very similar to those using level markup, as reported in Appendix Figure A6.

Contemporary policies, such as trade liberalization and SOE reform, may have an impact on firms' markup (Lu and Yu, 2015; Fan et al., 2018; Liu and Ma, 2021). However, they are unlikely to drive our main results during this period because these policies did not particularly target the SARS-hit provinces; they also had different timing from the SARS shock. Moreover, our estimation is based on within-industry comparison, hence policies such as industry-specific trade liberalization are unlikely to drive our main results.

Alternative Markup Measures. We estimate our model using the four alternative markup measures based on costs of good sold, capital user costs, raw markup, and the production approach, as discussed in Section 4.1. The results are consistent in all cases, as reported in Appendix Table A4 and Figures A7, A8, and A9. In particular, SARS substantially reduced the markup of firms in affected areas relative to firms in other areas; inventory and demand uncertainty, as an important channel, reduced the markup of affected firms by 1.0-1.7 percentage points, which is quantitatively consistent with the main results.

External Validation: Producer Price Index (PPI). We provide an external validation of the estimated effect of the SARS shock on markup, by examining the impact of SARS on PPI. We collected province-level PPI data from the China Statistical Yearbooks, which are officially published by the China Statistics Press of the National Bureau of Statistics of China.[18] We collected 269 PPI observations for 31 provinces from 1999 to 2007.[19] Using the PPI data, we estimate the impact of SARS on the province-level PPI using a similar difference-in-differences approach as in our main analysis, after controlling for province and year fixed effects and province-level GDP per capita and export share. As reported in Table 3[20], SARS reduced the PPI of firms in SARS-hit provinces by 8.7 percent relative to firms in other provinces, which is close to the impact of SARS on markup in our main results (7.8 percentage points). This effect is also long-lasting, as reported in Figure A10.

The relative changes in PPI and markup also have some implications to the mechanism. Because PPI and markup decreased by almost the same magnitude, it implies that the marginal cost remained almost unchanged after the SARS shock. Because the supply shock would typically drive up the production costs, the results suggest that SARS was more likely to be a dominant demand shock, instead of supply shock.

Discussion: potential sources of long-lasting effect. The long-lasting effects on market power suggest that the temporary SARS shock may have changed some fundamental factors in the market. SARS may have changed the uncertainty of demand, consumer preference, and the inventory strategy of firms in areas affected by SARS. Moreover, market friction exists. Therefore, after the negative SARS shock, it may be difficult for firms to recapture the lost consumers afterward. These factors result in a change in the market structure in the economy. As supporting evidence, we find that SARS substantially reduced the industry-level market share of firms in the the SARS-affected provinces; it also reduced the share of the number of firms by industry in the SARS-affected provinces. As shown in

[18]The China Statistical Yearbooks are available on the website of the National Bureau of Statistics of China: http://www.stats.gov.cn/english/Statisticaldata/AnnualData/.

[19]The data are not available for Hainan before 2001 and Tibet before 2005. We also do not cover Hong Kong Special Administrative Region and Macao Special Administrative Region due to data availability.

[20]We use weighted least squares and the total number of firms in the province in each year as the weight to be consistent with our main specification. The results are also similar when province GDP is used as the weight or ordinary least squares is used.

Appendix Figures A11 and A12, these effects are long-lasting and can potentially contribute to the long-lasting effects of SARS on market power and firms' inventory holding. Although we are not able to identify the contribution of each of the above factors separately due to data limitations, in the Appendix D we show that at least in the numerical model, a temporary SARS shock (as a negative shock on demand level and an increase of demand uncertainty) can generate long-term effects through market friction and changes in demand uncertainty.

5.2 Impact of SARS on Inventory and Demand Uncertainty

Table 4 reports the impact of the SARS epidemic on the inventory ratio and demand uncertainty based on the baseline specification (14). As shown in columns (1)-(3), the SARS epidemic substantially increases the inventory ratio of firms located in the four SARS-hit provinces, by 1.3-1.4 percentage points (or 11%), relative to that of firms in other provinces. This result suggests that as a large negative shock, SARS had a large impact on the demand faced by firms, which led to accumulation of inventories.[21]

The SARS epidemic also substantially increased the demand uncertainty faced by the firms in the SARS-affected areas. Columns (4)-(6) in Table 4 show that the demand uncertainty faced by these firms increased by 0.004, or 14% of a standard deviation, in response to the SARS shock, relative to the unaffected firms. This reflects that the SARS epidemic may have changed the purchasing behavior of buyers (consumers or downstream firms), which made the demand faced by firms more volatile and resulted in a higher level of demand uncertainty. All these results are robust after controlling for firm size and export effects.

The effects are also long-lasting, as reported in Figure 3(b) and 3(c). Interestingly, both the inventory ratio and demand uncertainty started to increase since 2002, followed by another increase in 2003. In Section 6, we show that the early response was completely driven by Guangdong province, where the SARS epidemic started earlier at the end of 2002. Following

[21]The increase in inventory after SARS is consistent with a rational story where the actual demand uncertainty increases or a behavioral story where the perceived demand uncertainty increases following the shock. We appreciate an anonymous referee for pointing this out.

the initial big jumps in 2002 and 2003, the effect continued to accumulate to 1.90% for inventory ratio and 0.69% for demand uncertainty in 2006. Both started to decrease in 2007. Presumably, the increased fear among consumers caused by the SARS shock did not vanish, at least during our data period, resulting in a long-term impact of SARS on demand uncertainty. Because demand uncertainty reduces markup, as predicted by our model and confirmed by the empirical evidence, the increased demand uncertainty may have (partially) contributed to the long-term effect of SARS.

The impact of SARS on markup, inventory, and demand uncertainty in our sample was not driven by a few extreme industries. Instead, it was the universal response by almost all industries. In Figure A13, we estimate an extended version of equation (14), by allowing SARS to have heterogeneous effects on each 2-digit industry. Almost all industries experienced a decline in markup and an increase in inventory following the SARS shock, although the magnitudes of the changes may differ. Most industries also experienced an increase in demand uncertainty, although the effect may not be significant for some industries, such as beverages and metal products. In general, our main results are robust at the industry level.

5.3 Mechanism: The Role of Inventory and Demand Uncertainty

Because higher inventory and demand uncertainty may reduce markup, as theoretically shown in Section 3 and empirically demonstrated in Section 4.3, the increased inventory and demand uncertainty may have played a role in the redistribution of market power caused by SARS. To verify this possibility, we use the Baron and Kenny (1986) causal steps approach and estimate an extended version of (14) by further controlling for inventory and demand uncertainty.[22]

Table A5 reports the estimation results. As expected, both the BOY inventory and demand uncertainty have negative effects on markup. More importantly, the estimated effect of

[22]Of course, although the method has been widely used in the literature (Alesina and Zhuravskaya, 2011), one caveat is that the Baron and Kenny (1986) causal steps approach may be biased, especially when there are omitted confounding factors or the mechanism variable is measured with error (Edwards and Lambert, 2007; Hayes, 2009). Hence the result should be treated as suggestive, in addition to our model prediction.

SARS on firm markup decreases substantially to 5.8 percentage points, after controlling for inventory and demand uncertainty in column (4). This implies that the SARS-induced increase in inventory and demand uncertainty may have contributed to the SARS effect on market power, by reducing the markup of SARS-hit firms by 2 percentage points (or 26% of the SARS effect on markup) relative to other firms. This result is consistent with an alternative decomposition based on (10) in our model, as discussed in detail in Appendix E.

6 Different Timing and Severity

This section uses the differential timing and severity of SARS in different provinces to provide further causal evidence on the relationship between SARS and market power.

6.1 Timing

The SARS epidemic first hit Guangdong in the fourth quarter of 2002, and it then gradually spread to other provinces in the first quarter of 2003, as discussed in Section 2. This different timing of SARS outbreaks between Guangdong and other affected provinces provides variation to test the causal effect of the SARS epidemic on firm performance.

We estimate (15) using two subsamples of our data separately. The first subsample keeps Guangdong as the SARS-affected province but excludes the other three heavily hit provinces (Beijing, Shanxi, and Inner Mongolia). The second subsample, instead, excludes Guangdong but keeps the other three heavily hit provinces (Beijing, Shanxi, and Inner Mongolia). Using this subsample, we estimate the timing of the impact of SARS on the three heavily hit provinces and expect that the impact first emerged in 2003.

Figure 4(a) presents the differential timing of the effect of SARS on the inventory ratio for firms in Guangdong and the other provinces that were hit heavily by SARS. Figure 4(a) and 4(b) show that the inventory ratio and demand uncertainty of firms located in Guangdong responded immediately after the outbreak in 2002, relative to the unaffected firms. In contrast, the inventory ratio and demand uncertainty of firms in the other three affected provinces did not increase until 2003, when SARS hit those provinces.

This differential timing of the impact of SARS in Guangdong and the other SARS-affected provinces provides further support on the causal effect of SARS on firm inventory and demand uncertainty. Interestingly, we find no differential timing of impact on markup in these two groups—both happened in 2003. Our conjecture is that prices are typically pre-announced and sticky. It takes time for firms to adjust prices, so firms may not have been able to adjust prices immediately in 2002 after the SARS outbreak in November in Guangdong.

6.2 Severity

Although we chose the four provinces that were hit hardest by SARS as the treated group for our main analysis, they experienced different levels of SARS severity. Beijing (2,772 cases) and Guangdong (1,520 cases) had the most cases, while Shanxi (475 cases) and Inner Mongolia (317 cases) had relatively fewer infections. Moreover, other provinces in China were also hit by SARS, although to a much lighter degree (mostly fewer than 10 cases in each province). We estimate the following equation to test the impact of SARS severity:

$$Y_{j,t} = \beta_0 + \beta_{100cases*SARS}(100Cases_j * SARS_{j,t}) + \beta_\Gamma \Gamma_{j,t} + \beta_z Z_{city,t} + \lambda_{city} + \lambda_{ind} + \lambda_t + \epsilon_{j,t}, \quad (16)$$

where $100Cases_j$ represents the total number of infected cases (unit: 100 cases) in the province where firm j is located.[23] All other variables and parameters are the same as previously defined in (14). The parameter of interest, $\beta_{100cases*SARS}$, measures the impact of 100 more infected cases on firm performance.

[23]We use the number of confirmed cases, instead of its percentage in the population, as the measure of SARS severity for two reasons. First, the number of SARS cases by province was reported in all news and emphasized by all levels of government during the epidemic, regardless of the province's size. The public, consumers, and firms were more sensitive to the total number of confirmed cases when making decisions, instead of the percentage of the population. Second, the government took the absolute number of cases very seriously. Lockdown and related policies were adopted mainly based on how many cases a province had, instead of the percentage of the population. Once a province reports a particular number of SARS cases, the province may choose to implement strict epidemic-control policies or even lockdown. The total number of confirmed cases was the measure that affected the decisions of consumers, firms, and government policies.

The results are reported in Table 5. Consistent with the results in Tables 2 and 4, the SARS epidemic had a substantial impact on market power, inventory, and demand uncertainty. An increase of 100 cases of infection in one province reduced the markup of firms in this province by 0.46 percentage point on average, lifted their inventory ratio by 0.08 percentage point, and had a statistically significant impact on demand uncertainty.

Consistent with our main results with the choice of the four provinces as the treatment group, the overall effects of SARS were mostly driven by the effects in the provinces that were hit hardest. For example, in Beijing with 2,772 cases, the SARS shock reduced the markup of firms by 12.75 percentage points ($0.46 \times 27.72 = 12.75$), increased the inventory ratio by 2.22 percentage points ($0.08 \times 27.72 = 2.22$) demand uncertainty by 0.0055 ($0.0002 \times 27.72 = 0.0055$), which accounts for 20% of a standard deviation of demand uncertainty. In provinces in the control group, which had fewer cases, the effect was negligible. The strong heterogeneous impacts of SARS based on the levels of severity of the epidemic further support the causality between the SARS shock and firm performance.

Finally, comparing columns (1) and (4) in Table 5 shows that the estimated negative effect per 100 SARS cases on firm markup decreased from 0.46 to 0.36 percentage point after controlling for the BOY inventory and current demand uncertainty. This implies that inventory dynamics and demand uncertainty may have served as an important mechanism. For example, they contributed to a reduction in markup by about 2.77 percentage points in Beijing[24] and 1.52 percentage points in Guangdong.

7 Who Gained (Lost) More Market Power?

Firms in Neighboring Provinces. One hypothesis is that firms that are geographically close to the SARS-hit provinces may have benefited from the reduced market power of the SARS-hit firms. This is because, on the one hand, these firms were more likely to be closer to or even share the markets of the SARS-hit firms. On the other hand, the geographically closer firms were also more likely to have similar industries to the SARS-hit firms due to

[24] This is calculated as $(0.46 - 0.36) \times 2772/100 \approx 2.77$ percentage points.

similar comparative advantages or industry clustering, making it easier for them to take the latter's market share following the SARS shock. We define neighboring provinces as provinces that share a border with one of the four SARS-hit provinces but that had fewer than 10 cases of SARS.[25] We add the interaction term Neighbor*SARS in addition into our main regression (14) to examine the potential benefit to neighboring provinces.

We find that firms in the neighboring provinces increased market power following the SARS shock, as demonstrated by the positive coefficient on $Neighbor * SARS$ in column (1) in Table A6. This result echoes the relatively increased market share of firms in the neighboring provinces, as reported in column (2).[26] Moreover, we also find that the neighboring firms experienced a decline in inventory following the SARS shock relative to the control group, consistent with the hypothesis that these firms were taking the market share of the SARS-affected firms. These results indicate that the SARS epidemic might have redistributed market power and market share from the treated provinces to the neighboring provinces.

Industry Heterogeneity. Figure A13 demonstrates that SARS may have had heterogeneous impacts on different industries. To understand the nature of the heterogeneity, we explore what types of industries were subject to larger impacts from SARS. First, SARS had a larger effect on inventory and demand uncertainty in industries producing final goods instead of intermediate goods, as shown in Table A8, although the impact on markup is not statistically different. One possibility is that demand in final goods industries is more volatile relative to intermediate industries. Second, industries with higher demand uncertainty before SARS, as measured by the standard deviation of the constructed demand shocks, were subject to a larger effect on inventory and markup, as shown in Table A9. This further supports that inventory and demand shocks play an important role in explaining the impact of SARS.

[25]We require fewer than 10 SARS cases to define neighboring provinces to rule out the possibility that some provinces sharing border with the four treated provinces may have (slightly) more SARS cases than other control provinces. Following this definition, the neighboring provinces include Hunan, Jiangxi, Fujian, Gansu, Ningxia, Liaoning, and Heilongjiang. When dropping the other neighboring provinces with more than 10 SARS cases from the control group to ensure a cleaner control group, the results are robust as in Table A7.

[26]The market share is defined as the share of total sales of all firms in the province in a 4-digit industry relative to the national sales of that industry. So, in this regression the original firm-level observations are collapsed into the province-industry-year level, resulting in 67,753 observations.

Firm Heterogeneity. Table A10 tests the heterogeneous SARS effects on firms of different sizes. The negative triple interaction coefficient shows that larger firms in the SARS-affected areas suffered a greater loss of market power than smaller ones. Appendix Figure A14 further plots the changes in markup of SARS-affected firms from 2001 to 2005 against their markup in 2001, the year before the SARS outbreak. The negative correlation shows that high-markup firms lost more market power after SARS. This makes sense because larger and typically high-markup firms usually sell to markets that are more distant, and thus would be more seriously affected by the SARS shock and the resulting policies to fight against SARS.[27]

8 Discussion and Robustness Checks

This section discusses alternative explanations and robustness checks to secure our results.

Demand versus Supply Shock. In principle both demand and supply shocks may exist during the SARS shock. Our model, measures, and empirical strategy are consistent with both and we don't have to take a stand on whether it is a demand or supply shock.[28] However, our multiple sources of evidence suggest that demand shock is the dominant force and that's why we built our model in that way. First, the inventories of both intermediates and outputs increased substantially as shown in Table A11 and Figure A15, which is consistent with a dominant negative demand shock story. Second, the PPI of SARS-affected firms declined, which contradicts with the supply shock theory which increases production costs. Moreover, PPI and markup declined by almost the same magnitude, suggesting that there are no significant changes in marginal costs. All this evidence is consistent with Hassan et al. (2023) who find that SARS is mainly a demand shock to firms using textual analysis.

Firm Fixed Effects. We test the robustness by including firm fixed effects in our main model (14) and (15). Accordingly, we dropped the city and industry fixed effects, because

[27]The heterogeneous effect on SARS may have interesting implications on the aggregate markup, as implied in Edmond et al. (2023). However, because our difference-in-differences analysis does not capture the potential equilibrium effect, we refrain from discussing the overall impact on aggregate markup, although SARS is likely to reduce the nationwide aggregate markup.

[28]Our theoretical model and the measurement of markup are still valid in the presence of supply shocks. This can be seen by adding an unexpected productivity shock to the production function, similar to adding the demand shock to the demand function in the model.

very few firms changed location or industry during our data period. The estimation results are reported in Table A12 and Figure A16, and they are consistent with the main findings.

Alternative Classification of the Treated group. In our main analysis, we use four provinces, Beijing, Guangdong, Inner Mongolia, and Shanxi, as the treated provinces. In this robustness check, we re-estimate the model using more provinces (Beijing, Guangdong, Shanxi, Inner Mongolia, Hebei, and Tianjin) as the treatment group. We find robust results reported in Appendix Table A13 and Figure A17.

Alternative Specifications. Our baseline analysis allows SARS to influence Guangdong and the other three treated provinces at different years. In this robustness check, we use a uniform cutoff of the treatment year and define $SARS_t$ equals 1 if year$\geq$ 2003 for all provinces; $SARS_t = 0$ otherwise. The results are robust, as shown in Table A14. Moreover, when using the relative time periods to SARS shock as a potential solution to the staggered DID problem (Sun and Abraham, 2021), results are also robust, as shown in Figure A18.

Inventory of Finished Goods. We used total inventory in the baseline analysis, which includes the inventory of intermediate goods, work in process, and finished goods. This section shows that our results are robust when using the inventory of finished goods, which is similarly defined using finished inventory as: $\frac{RFinishedInventory_{j,t}}{RFinishedInventory_{j,t-1}+Routputs_{j,t}}$. We use it to re-estimate the demand elasticity and the "not-stockout probability" $G(\cdot)$. All other steps follow similarly. Table A15 and Figure A19 show that the results are robust.

9 Conclusion

This paper examined the impact of serious epidemics on the market power of manufacturing firms and investigated the potential role played by inventory and demand uncertainty, using the 2003 SARS epidemic in China as a natural shock. We first showed how a firm's market power is linked to its inventory stock and demand uncertainty in a stylized model, by influencing the firms' dynamic production and pricing decisions. The model implies the necessity of accounting for the heterogeneity of inventory stock and demand uncertainty to understand markup and provides a straightforward measurement.

Empirically, SARS reduced the markup of firms located in the four hardest-hit provinces by 7.8 percentage points, relative to other firms. The SARS-induced increase in inventory and demand uncertainty may have served as an important mechanism. Moreover, although the SARS epidemic was considered a temporary health shock, it had a long-lasting effect on firms' market power. This long shadow of SARS suggests that the temporary shock may have changed some of the economic fundamentals, such as consumer preference, demand uncertainty, firms' customer base, and their production and inventory strategy.

Our results may be applied to other types of epidemics and pandemics (e.g., COVID), suggesting that they may have a large and long-lasting impact on the redistribution of market power across firms. As Hassan et al. (2023) shows, COVID might have a larger impact on the supply side besides its impact on demand. Moreover, the COVID shock was even larger and lasted much longer, therefore it might have a deeper impact on the economy and the general equilibrium effect could be important. The evaluation of other serious epidemics and pandemics (e.g., COVID) may have to consider these differences.

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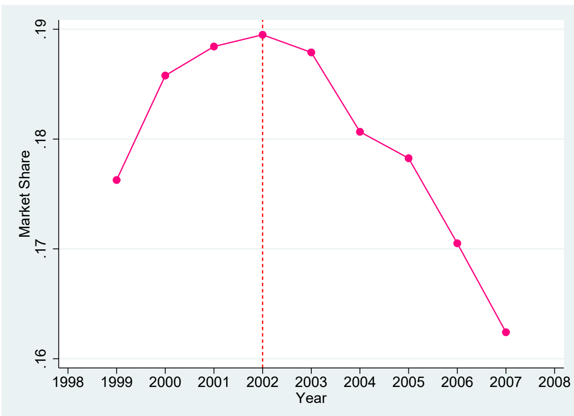
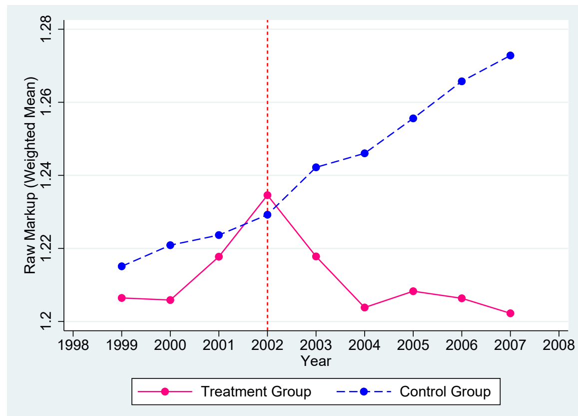
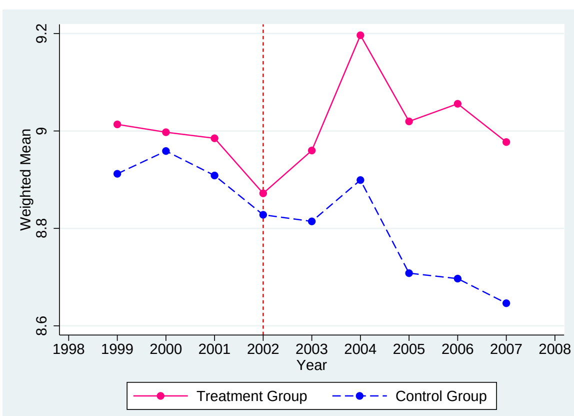
Figure 1: Comparison of market share, raw markup, and inventories in the treatment and control groups



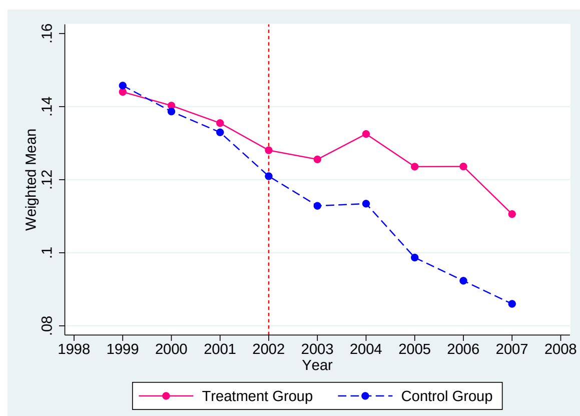
(a) Market Share of Treated Provinces



(b) Raw Markup



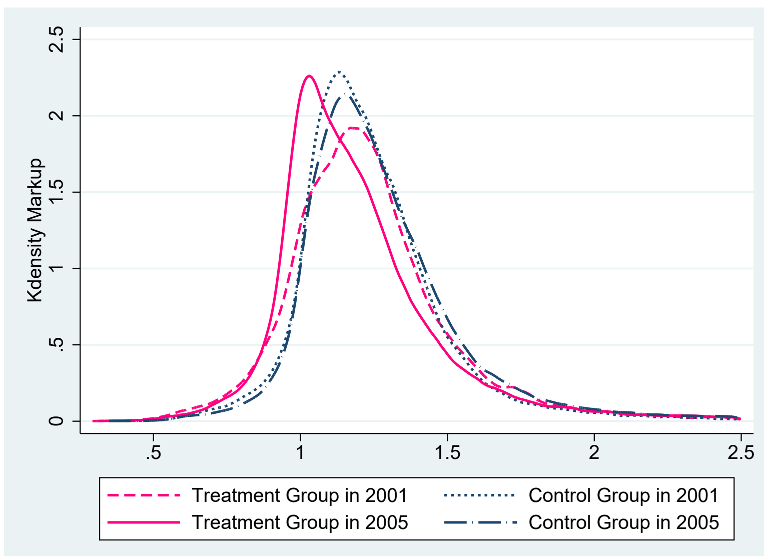
(c) Inventory Level (log)



(d) Inventory Ratio

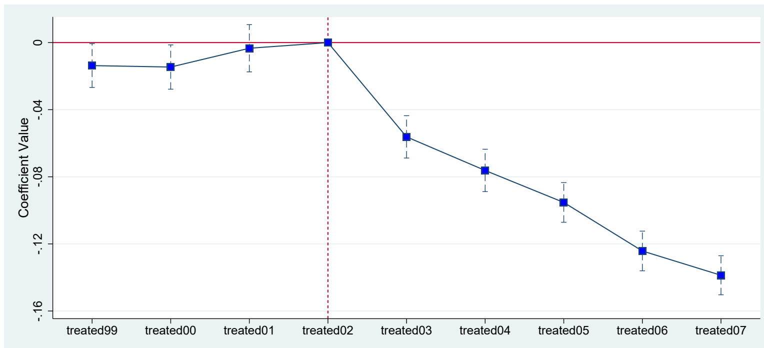
Note: Revenue-weighted mean in Figure 1(b), 1(c), and 1(d) . The patterns are similar for the median and simple mean.

Figure 2: Comparison of the markup distribution in the treatment and control groups in 2001 and 2005

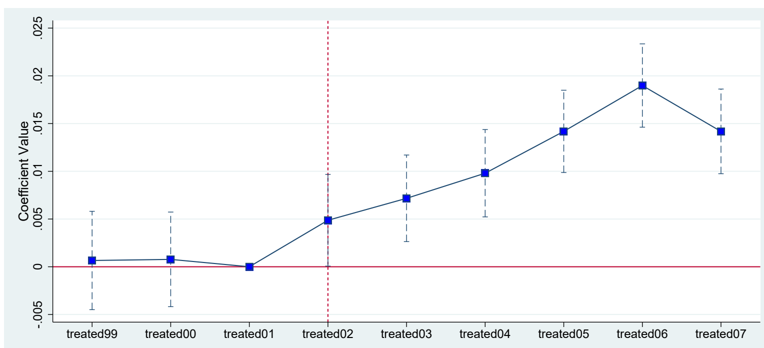


Note: The pattern is similar for the balanced panel.

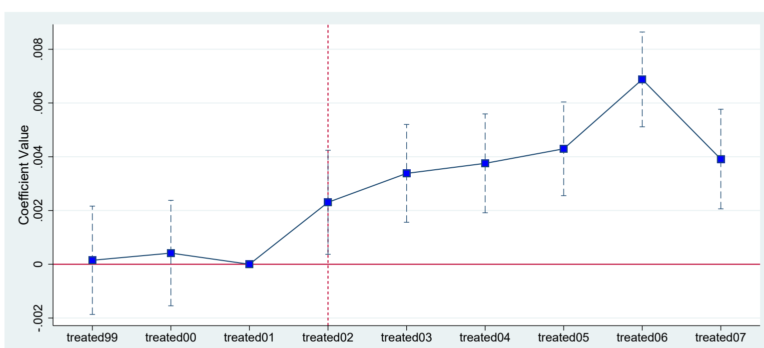
Figure 3: Dynamic effects of SARS on markup, inventory ratio, and demand uncertainty: $\beta_{treated*t}$



(a) Markup



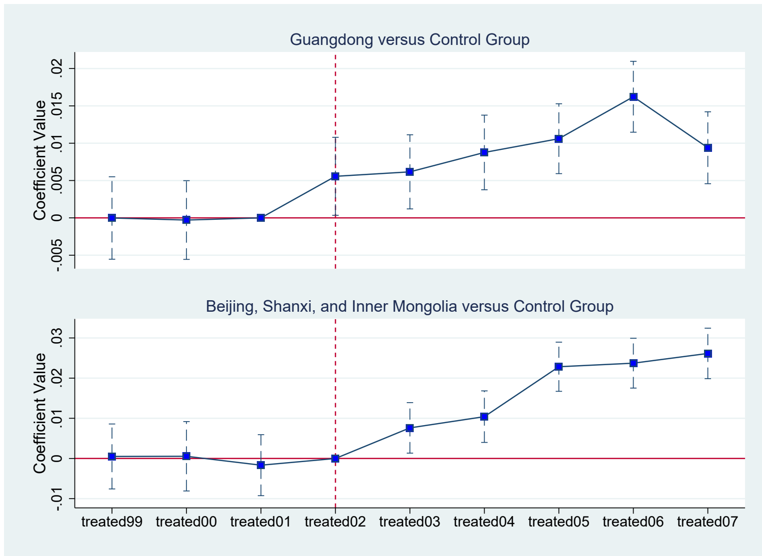
(b) Inventory Ratio



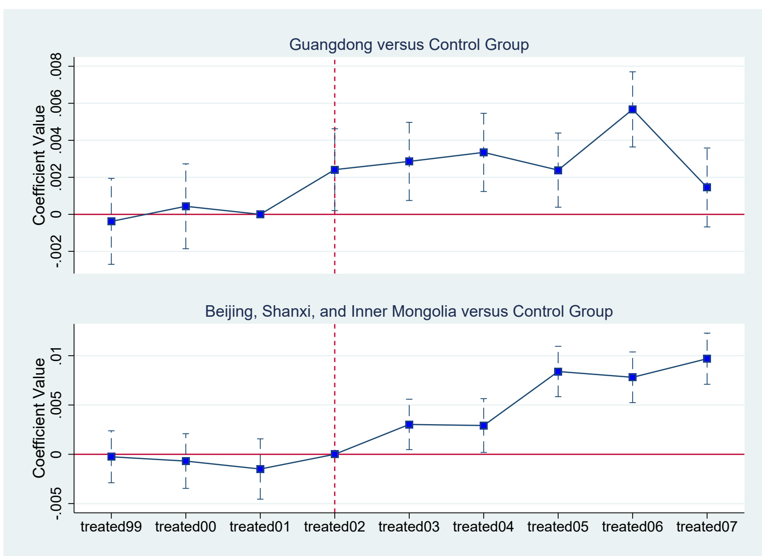
(c) Demand Uncertainty

Note: The range represents the 95% confidence intervals of the parameter estimates.

Figure 4: Further supporting evidence: Different timing of SARS outbreaks



(a) Inventory Ratio



(b) Demand Uncertainty

Note: The range represents the 95% confidence intervals of the parameter estimates.

Table 1: Empirical Test of the Conjectures

	Markup			Markup (Log)		
	(1)	(2)	(3)	(4)	(5)	(6)
L.Inventory Ratio	-0.204***		-0.202***	-0.142***		-0.141***
	(0.005)		(0.005)	(0.004)		(0.004)
Demand Uncertainty		-0.225***	-0.213***		-0.188***	-0.177***
		(0.017)	(0.020)		(0.011)	(0.013)
Firm Size (K)	YES	YES	YES	YES	YES	YES
Firm Export Status	YES	YES	YES	YES	YES	YES
Firm Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Observations	846,270	1,234,011	839,558	846,270	1,234,011	839,558
Adjusted R^2	0.371	0.358	0.371	0.406	0.392	0.406

Note: Standard errors (clustered at the firm level) are in parentheses.

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 2: Impacts of the SARS Epidemic on Firm Markup

	Markup			Markup (Log)		
	(1)	(2)	(3)	(4)	(5)	(6)
Treated*SARS	-0.078***	-0.078***	-0.078***	-0.057***	-0.057***	-0.057***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Firm Size (K)		YES	YES		YES	YES
Firm Export Status			YES			YES
City Export Share			YES			YES
City Population Density	YES	YES	YES	YES	YES	YES
City GDP Per Capita	YES	YES	YES	YES	YES	YES
Industry, city, and year FEs	YES	YES	YES	YES	YES	YES
Observations	1,208,577	1,208,577	1,208,577	1,208,577	1,208,577	1,208,577
Adjusted R^2	0.102	0.102	0.103	0.110	0.110	0.111

Note: Standard errors (clustered at the city-industry-year level) are in parentheses.

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 3: Impact of the SARS Epidemic on the Producer Price Index

	Producer Price Index	
	(1)	(2)
Treated*SARS	-0.088***	-0.087***
	(0.023)	(0.020)
Province Export Share		YES
Province GDP Per Capita		YES
Province Fixed Effects	YES	YES
Year Fixed Effects	YES	YES
Observations	269	269
Adjusted R^2	0.754	0.757

Note: Weighted least squares is used and the total number of firms in the province in each year is used as the weight.

Standard errors are clustered at the province-year level and reported in parentheses.

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 4: Impacts of the SARS Epidemic on the Inventory Ratio and Demand Uncertainty

	Inventory Ratio			Demand Uncertainty		
	(1)	(2)	(3)	(4)	(5)	(6)
Treated*SARS	0.013***	0.014***	0.014***	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Firm Size (K)		YES	YES		YES	YES
Firm Export Status			YES			YES
City Export Share			YES			YES
City Population Density	YES	YES	YES	YES	YES	YES
City GDP Per Capita	YES	YES	YES	YES	YES	YES
Industry, city, and year FEs	YES	YES	YES	YES	YES	YES
Observations	1,208,577	1,208,577	1,208,577	1,201,194	1,201,194	1201194
Adjusted R^2	0.120	0.134	0.135	0.394	0.394	0.394

Note: Standard errors (clustered at the city-industry-year level) are in parentheses.

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 5: Further Supporting Evidence: SARS Severity

	Markup	Inventory Ratio	Demand Uncertainty	Markup
	(1)	(2)	(3)	(4)
100Cases*SARS	-0.0046***	0.0008***	0.0002***	-0.0036***
	(0.0002)	(0.0001)	(0.0000)	(0.0002)
L.Inventory Ratio				-0.3709***
				(0.0035)
Demand Uncertainty				-0.1545***
				(0.0170)
Observations	1,208,577	1,208,577	1,201,194	827,753
Adjusted R^2	0.103	0.135	0.394	0.121

Note: Standard errors (clustered at the city-industry-year level) are in parentheses. Controlled for firm-level size (capital) and export status, city-level export share, population density, and GDP per capita, and the industry, city, and year fixed effects.

* $p < .10$, ** $p < .05$, *** $p < .01$

Appendices

(For Online Publication Only)

A Derivations of the Model

In this appendix, we show step by step how the key equations in the main text are derived.

A.1 Price Elasticity of Expected Sales

We define the price elasticity of expected sales as $\varepsilon_t \equiv \frac{\partial E_t(z_t)}{\partial p_t}\frac{p_t}{E_t(z_t)}$. Given the definition of expected sales($E_t(z_t) = \int_{-\infty}^{Q_t}[h(p_t)+u_t]\,dG(u_t) + \int_{Q_t}^{\infty}(n_{t-1}+y_t)\,dG(u_t)$), and the definition of price elasticity of demand ($e_t \equiv \frac{\partial h(p_t)}{\partial p_t}\frac{p_t}{h(p_t)}$). We can derive the relationship between price elasticity of demand and the price elasticity of expected sales (effective demand elasticity) as follows.

$$
\begin{aligned}
\varepsilon_t \quad & \equiv \frac{\partial E_t(z_t)}{\partial p_t}\frac{p_t}{E_t(z_t)} \\
&= \left\{[h(p_t)+Q_t]g(Q_t)\frac{\partial Q_t}{\partial p_t} + \frac{\partial h(p_t)}{\partial p_t}\int_{-\infty}^{Q_t} g(u_t)\,du_t - [n_{t-1}+y_t]g(Q_t)\frac{\partial Q_t}{\partial p_t}\right\}\frac{p_t}{E_t(z_t)} \\
&= \frac{\partial h(p_t)}{\partial p_t}\frac{p_t}{E_t(z_t)}\int_{-\infty}^{Q_t} g(u_t)\,du_t \\
&= \frac{\partial h(p_t)}{\partial p_t}\frac{p_t}{h(p_t)}\cdot\frac{h(p_t)\int_{-\infty}^{Q_t} g(u_t)\,du_t}{E_t(z_t)} \\
&= e_t\cdot\frac{h(p_t)G(Q_t)}{E_t(z_t)}
\end{aligned} \tag{A.1}
$$

A.2 The Optimal Decisions

Observing its beginning-of-year inventories carried over from last period and firm-level characteristics, each period, the firm chooses price p_t and production y_t to maximize the present discounted expected value of profits.

$$
\begin{aligned}
\max_{y_t,p_t} \quad & E_t\left\{\sum_{s=t}^{\infty}\beta^{s-t}(p_s z_s - C_Y(y_s) - C_N(n_{s-1}))\right\}, \\
\text{subject to:} \quad & (2),\ (3) \text{ and } (4).
\end{aligned}
$$

The standard dynamic programming techniques are employed to solve the firm's profit maximization problem. The dynamic programming equation can be expressed as

$$\begin{aligned} V(n_{t-1}) = \max_{y_t, p_t} \quad & E_t \left\{ p_t z_t - C_Y(y_t) - C_N(n_{t-1}) + \beta V(n_t) \right\}, \\ \text{subject to:} \quad & (2),\ (3) \text{ and } (4). \end{aligned}$$

Given the distribution of demand shocks, the dynamic programming equation can be written as:

$$\begin{aligned} V(n_{t-1}) = \max_{y_t, p_t} \{ p_t E_t(z_t) - C_Y(y_t) - C_N(n_{t-1}) \\ + \beta \left[\int_{-\infty}^{Q_t} V[n_{t-1} + y_t - h(p_t) - u_t] \, dG(u_t) + \int_{Q_t}^{\infty} V(0) \, dG(u_t) \right] \right\} \end{aligned} \tag{A.2}$$

The first order condition with respect to production decision is:

$$\begin{aligned} p_t \left\{ [h(p_t) + Q_t] \, g(Q_t) \frac{\partial Q_t}{\partial y_t} - (n_{t-1} + y_t) g(Q_t) \frac{\partial Q_t}{\partial y_t} + \int_{Q_t}^{\infty} g(u_t) \, du_t \right\} \\ - C_Y'(y_t) + \beta \left[V(0) g(Q_t) \frac{\partial Q_t}{\partial y_t} + \int_{-\infty}^{Q_t} V'(n_t) \, dG(u_t) - V(0) g(Q_t) \frac{\partial Q_t}{\partial y_t} \right] \end{aligned} \tag{A.3}$$

After re-arrangement, we can get:

$$p_t \left[1 - G(Q_t) \right] - C_Y'(y_t) + \beta \int_{-\infty}^{Q_t} V'(n_t) \, dG(u_t) = 0 \tag{A.4}$$

We yield the first order condition of price as follows:

$$E_t(z_t) + \frac{\partial E_t(z_t)}{\partial p_t} p_t - \frac{\partial h(p_t)}{\partial p_t} \beta \int_{-\infty}^{Q_t} V'(n_t) \, dG(u_t) = 0 \tag{A.5}$$

After re-arrangement, we can get:

$$1 + \underbrace{\frac{\partial E_t(z_t)}{\partial p_t} \frac{p_t}{E_t(z_t)}}_{\varepsilon_t} - \underbrace{\frac{\partial h(p_t)}{\partial p_t} \frac{p_t}{h(p_t)} \frac{h(p_t) G(Q_t)}{E_t(z_t)}}_{\varepsilon_t} \cdot \frac{\beta \int_{-\infty}^{Q_t} V'(n_t) \, dG(u_t)}{p_t \cdot G(Q_t)} = 0 \tag{A.6}$$

Or,

$$\mu_t = \frac{\varepsilon_t}{1 + \varepsilon_t} = \frac{p_t}{\frac{\beta \int_{-\infty}^{Q_t} V'(n_t) \, dG(u_t)}{G(Q_t)}} \tag{A.7}$$

Combing both the first order conditions of price and production, we can get:

$$\mu_t = \frac{\varepsilon_t}{1 + \varepsilon_t} = \frac{p_t G(Q_t)}{C_Y'(y_t) - p_t [1 - G(Q_t)]}. \tag{A.8}$$

A.3 The Euler Equation

Employing the envelop theorem, we can get that:

$$
\begin{aligned}
V'(n_{t-1}) \quad &= \{p_t\left[1-G(Q_t)\right]-C'_Y(y_t)\}\frac{\partial y_t}{\partial n_{t-1}}-C'_N(n_{t-1})-\left[E_t(z_t)+p_t\frac{\partial E_t(z_t)}{\partial p_t}\right]\frac{\partial p_t}{\partial n_{t-1}}\\
&+\beta\int_{-\infty}^{Q_t}V'(n_t)(1+\frac{\partial y_t}{\partial n_{t-1}}-\frac{\partial h(p_t)}{\partial p_t}\frac{\partial p_t}{\partial n_{t-1}})\,dG(u_t)\\
&= -C'_N(n_{t-1})+\beta\int_{-\infty}^{Q_t}V'(n_t)\,dG(u_t) \qquad \text{(A.9)}
\end{aligned}
$$

where the second equality comes from the combination of first order conditions of production and price.

B Details about Detrending

This appendix provides the details of detrending the dependent variables (markup, inventory ratio, and demand uncertainty) following Rambachan and Roth (2023). Specifically, we detrend markup in the first step by estimating the following equation,

$$
\begin{aligned}
\mu_{j,t} \quad = \quad & \beta_0+\beta_{Tyear*BJ}(Tyear_t*BJ_j)+\beta_{Tyear*GD}(Tyear_t*GD_j)+\beta_{Tyear*SX}(Tyear_t*SX_j)\\
&+\beta_{Tyear*NM}(Tyear_t*NM_j)+\beta_{Tyear*Control}(Tyear_t*Control_j)+\beta_\Gamma\Gamma_{j,t}+\beta_z Z_{city,t}\\
&+\lambda_{city}+\lambda_{ind}+\lambda_t+\epsilon_{j,t}, \qquad \text{(B.1)}
\end{aligned}
$$

where $Tyear$ is the difference of year and 1998 that represents the year trend. BJ, GD, SX, NM, and $Control$ represent dummy variables indicating Beijing, Guangdong, Shanxi, Inner Mongolia, and the control provinces, respectively. All other variables and parameters are the same as previously defined in (14). We estimate (B.1) using data from 1999 to 2002. The pre-trend estimates are the according predicted year trend terms.

To detrend inventory ratio and demand uncertainty, considering that there is a different timing of SARS outbreaks between Guangdong and other affected provinces, in the first step we use a slightly different equation as follows:

$$
\begin{aligned}
Y_{j,t} \quad = \quad & \beta_0+\beta_{Tyear*GD*BF}(Tyear_t*GD_j*BF_t)+\beta_{Tyear*GD*AF}(Tyear_t*GD_j*AF_t)\\
&+\beta_{Tyear*SX}(Tyear_t*SX_j)+\beta_{Tyear*BJ}(Tyear_t*BJ_j)+\beta_{Tyear*NM}(Tyear_t*NM_j)\\
&+\beta_{Tyear*Control}(Tyear_t*Control_j)+\beta_\Gamma\Gamma_{j,t}+\beta_z Z_{city,t}+\lambda_{city}+\lambda_{ind}+\lambda_t+\epsilon_{j,t}, \text{(B.2)}
\end{aligned}
$$

where $Y_{j,t}$ refers to inventory ratio and demand uncertainty. BF_t equals 1 for year 1999, 2000, and 2001 and zero otherwise. AF_t equals 1 from 2002 and onward and zero otherwise. Using time dummies BF_t and AF_t we can manage the different timing of SARS outbreaks between Guangdong and other affected provinces when estimating the differential pre-trend of inventory ratio and demand uncertainty. All other variables and parameters are the same as previously defined in (B.1). We estimate (B.2) using data from 1999 to 2002. The pre-trend estimates for Guangdong is $\hat{\beta}_{Tyear*GD*BF}(Tyear_t*GD_j)$ where we only use the year trend parameter before the SARS outbreak in Guangdong to get the predicted year trend term. For the other three affected provinces and the control provinces, their pre-trend estimates are the according predicted year trend terms. Because prices are sticky we suppose that there is no differential timing of impact on markup, in the pre-trend regression of markup we do not include the additional time dummies BF_t and AF_t as in (B.1).

C Technical Details: Potential Source of Long-term Effect

Increased demand uncertainty in response to the shock of an epidemic may generate long-term effects on inventory and markup. In addition, change in inventory strategy may be another important contributing factor. Although SARS led to an increase in average inventory, some firms with a lean inventory strategy may have stocked out. As discussed in many industry reports, firms that stocked out right after SARS broke out may have dropped their lean inventory strategy and held more inventory, after realizing that the original lean inventory strategy may not be optimal given the possibility of a large demand shock. To explore such possibility, we compare the effect of SARS on the inventory dynamics of firms that stocked out right after the shock and those did not stock out, by estimating the following equation:

$$\begin{aligned} Inventory\ Ratio_{j,t} \quad = \quad & \beta_0 + \beta_{ST*treated*SARS}(ST_j * Treated_j * SARS_t) \\ & + \beta_{NST*treated*SARS}(NST_j * Treated_j * SARS_t) \\ & + \beta_{SARS*ST}(SARS_t * ST_j) + \beta_{treated*ST}(Treated_j * ST_j) + ST_j \\ & + \beta_{\Gamma}\Gamma_{j,t} + \beta_z Z_{city,t} + \lambda_{city} + \lambda_{ind} + \lambda_t + \epsilon_{j,t}, \end{aligned} \tag{C.1}$$

where ST_j is an indicator that equals 1 for all years if firm j stocked out right after the SARS shock.[29] $ST_j = 0$ for all other cases. We define $NST_j = 1 - ST_j$. We include dummy variable ST_j and the cross terms $SARS_t * ST_j$ and $Treated_j * ST_j$ in the regression. All other variables and parameters are the same as previously defined in (14). The parameters of interest are $\beta_{ST*treated*SARS}$ and $\beta_{NST*treated*SARS}$, which represent the effect of SARS on the inventory ratio of stockout firms and not-stockout firms, respectively.

Table A1 reports the estimation results. In the regression, we drop years 2002 and 2003 to avoid the possibility that the zero inventory ratio during stockout may bias the comparison. We find that after the epidemic, firms that stocked out right after the SARS shock increased their inventory more than other firms, by 1.6 and 1.2 percentage points, respectively.

In Figure A1, we further estimate an extended version of (C.1) by allowing SARS to have a flexible yearly effect on these two group of firms separately. We find that the inventory of firms that did not stock out right after the SARS shock jumped up in 2002 and 2003; then it remained stable at a high level until the end of our data period. On average, their inventory was about 1 percentage point higher than that before the SARS shock. In contrast, after the initial drop in 2002 and 2003, the inventory of firms that stocked out right after the SARS shock bounced back sharply to a much higher level. In 2004, their inventory

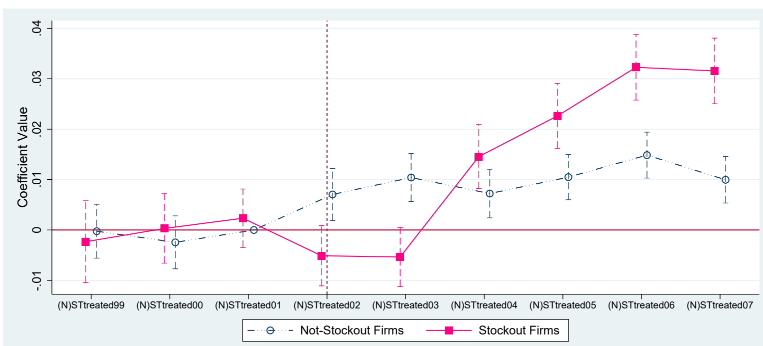
[29] As usual, we treat Guangdong and other affected provinces differently, because SARS hit them at different times. $ST_j = 1$ if firm j stocked out in 2002 or 2003 if it is in Guangdong, or if firm j stocked out in 2003 if it is located in provinces except Guangdong.

Table A1: Impact of SARS on Inventory: Stockout Firms versus Not-Stockout Firms

	Inventory Ratio
	(1)
ST*Treated*SARS	0.016***
	(0.003)
NST*Treated*SARS	0.012***
	(0.001)
SARS*ST, Treated*ST, and ST	YES
Firm Size (K)	YES
Firm Export Status	YES
City Export Share	YES
City Population Density	YES
City GDP Per Capita	YES
Industry Fixed Effects	YES
City Fixed Effects	YES
Year Fixed Effects	YES
Observations	984,025
Adjusted R^2	0.139

Note: Standard errors (clustered at the city-industry-year level) are in parentheses.
* $p < .10$, ** $p < .05$, *** $p < .01$

Figure A1: Source of the long-term effects of SARS on inventory: Stockout versus not-stockout firms



Note: The range represents the 95% confidence intervals of the parameter estimates.

increased by about 2 percentage points and it continued to increase until 2006 when it reached its maximum (over 3.2 percentage points higher than the control group). The surprisingly greater inventory accumulation for the initial stockout firms reflects that these firms may have changed their optimal inventory strategy and increased their long-term inventory level, after realizing that the lean inventory strategy may not have been optimal in a world with potentially large shocks. This explanation is supported by some expert reports in the industry (footnote 30 provides some examples).[30]

Comparing these results with these in Table 4 and Figure 3(b), we find that the long-term effect of SARS might be driven by firms that stocked out during the SARS epidemic, presumably because they changed their inventory management strategy after SARS and actively increased their inventory for a longer period.

D Model Extension: Serially Correlated Demand Shifter

In the main text, the model assumes i.i.d. demand shifter. However, the demand shifter could be serially correlated. Assume that the demand function is

$$x_t = \widetilde{h}(p_t) + \phi_t, \tag{D.1}$$

where the demand shifter (ϕ_t) follows an AR(1) process as follows:

$$\phi_t = \rho_0 + \rho_1 \phi_{t-1} + u_t, \tag{D.2}$$

where u_t is the innovation to demand shifter at period t and is i.i.d. with mean zero and standard deviation of σ_u. The demand function allows for a serially correlated demand shifter and can be rewritten as $x_t = h(\phi_{t-1}, p_t) + u_t$. Accordingly Q_t can be rewritten as $Q_t \equiv n_{t-1} + y_t - E_t(x_t) = n_{t-1} + y_t - h(\phi_{t-1}, p_t) = n_{t-1} + y_t - \widetilde{h}(p_t) - \rho_0 - \rho_1 \phi_{t-1}$. The firm's optimal decisions can be re-characterized in the following dynamic programming problem in recursive form:

$$\begin{aligned} V(\phi_{t-1}, n_{t-1}) = \max_{y_t, p_t} \quad & E_t \left\{ p_t z_t - C_Y(y_t) - C_N(n_{t-1}) + \beta V(\phi_t, n_t) \right\}, \\ \text{subject to:} \quad & (\text{D.1}),\ (\text{D.2}),\ (3),\ \text{and}\ (4). \end{aligned} \tag{D.3}$$

It is straightforward to show that all analysis in Section 3 and the markup measures in Section 4 still apply by replacing $h(p_t)$ by $h(p_t, \phi_{t-1})$, so is the empirical analysis in Section 4.3.

We first solve out firms' optimal decisions (y_t, p_t) and value functions $V(\phi_{t-1}, n_{t-1})$ given different states (ϕ_{t-1}, n_{t-1}) of the extended dynamic model. Based on the optimal solutions of the model, we show the relationships between firm markup, BOY inventory, and demand uncertainty, providing evidence to support the Conjecture 1 in the main text. Then we simulate the extended dynamic model and show that a temporary SARS shock can generate a long-lasting effect on market power through the mechanisms of serially correlated demand shifter, increased demand uncertainty, and firms' incentives to change inventory strategy

[30] For some expert reports on firms' change of inventory strategy after major shocks, see Brindley (2020), "Can Lean Manufacturing Work In a Post Covid-19 World?" Pallet Enterprise, September 1, available at: https://palletenterprise.com/view_article/5508/Can-Lean-Manufacturing-Work-In-a-Post-Covid-19-World? (accessed May 6, 2021); Leonard (2020), "Were Supply Chains Too Lean during the Pandemic? A Survey Shows an Industry Divided", Supply Chain Dive, September 29, available at: https://www.supplychaindive.com/news/Lean-supply-chain-slack-CSCMP-survey/586069/ (accessed May 6, 2021); and Hadwick (2020), "The End of Just-in-Time?" Reuters Events, July 3, available at: https://www.reutersevents.com/supplychain/supply-chain/end-just-time (accessed May 6, 2021) for examples.

after the shock.

We summarize the algorithm for solving the firm's dynamic problem as follows:

1. Pick a set of the reasonable parameterization, including the parameters of the demand elasticity, production costs functions, inventory costs function, AR(1) process of demand shifter, distribution of demand shocks.[31]
2. Discretize the state space, the lagged demand shifter (ϕ_{t-1}) and the BOY inventory (n_{t-1}), into S. $s_t = \{\phi_{t-1}, n_{t-1}\}$, $s_t \in S$. We chose 30 grids for demand shifter and 40 grids for inventory, respectively. The total number of state grids is $N = 30 * 40 = 1200$. Discretize the decisions, production (y_t) and price (p_t) in to A. $a_t = \{p_t, y_t\}$, $a_t \in A$. We chose 40 grids for production and 80 grids for price, respectively. Then the total number of decision grids is $N = 40 * 80 = 3200$. The state evolves according to a transition probability: $f(a, s, s') = \mathbb{P}\{s_{t+1} = s' | s_t = s, a_t = a\}$. The choice-specific value function could be expressed as follows:

$$
\begin{aligned}
& V\big(a_t = \{p_t, y_t\}, s_t = \{\phi_{t-1}, n_{t-1}\}\big) \\
= \quad & p_t \left\{ \int_{-\infty}^{Q_t} [\widetilde{h}(p_t) + \rho_0 + \rho_1 \phi_{t-1} + u_t] \, dG(u_t) + \int_{Q_t}^{\infty} (n_{t-1} + y_t) \, dG(u_t) \right\} \\
& - C_Y(y_t) - C_N(n_{t-1}) + \beta \sum_{s' \in S} V(s'_{t+1}) f(a_t, s_t, s'_{t-1})
\end{aligned}
\tag{D.4}
$$

3. Given the parameterization, for each discretized states $s \in S$, solve firms' optimal decisions ($a^* = \{p^*, y^*\}$) and the value function $V(s)$ of the dynamic problem (D.3), and compute the markup (μ) following (10).

   The algorithm to solve the dynamic model is as follows:

   Step 1: Pick an initial value of the value function $V_0(S)$.

   Step 2: Calculate the choice-specific value function $V(A, S)$ for each action $a \in A$ in each state $s \in S$ based on (D.4). The transition probability $f(a, s, s')$ can be computed by combining the demand shifter evolution process (D.2) with the accounting equation (4) that describes the inventory evolution process.

   Step 3: Update $V(A, S)$ to $V_1(S)$ using (D.3). For each state ($s \in S$) of $V_1(S)$ we have $V_1(s) = V(a^*, s)$ where $V(a^*, s) \geq V(a, s), \forall a \in A$.

   Step 4: If $|V_1(S) - V_0(S)| \geq 10^{-6}$, replace $V_0(S)$ by $V_1(S)$ and go back to step 2.

   Iterate until $|V_{i+1}(S) - V_i(S)|$ is small enough, so $V_i(S)$ converges to firm value function $V(S)$. This algorithm solves the firms' optimal decisions, value functions, and the corresponding firm markup based on (10) in the discretized state space point by point.
4. We use the quadratic spline to plot the relationship between the firm's BOY inventory state and its markup while fixing the other state variable, demand shifter, at its steady-state value. The results are shown in the black solid line in Figure A2.

[31] In the baseline of the numerical model, $\widetilde{h}(p_t) = p_t^e$, and the original price elasticity of demand ($e \equiv \frac{\partial h(\phi_{t-1}, p_t)}{\partial p_t} \frac{p_t}{h(\phi_{t-1}, p_t)}$) is set as -5.5. The demand shifter evolves as $\phi_t = 0.05 + 0.9 * \phi_{t-1} + u_t$, so the steady state value of demand shifter is 0.5. The demand shock u_{jt} follows a normal distribution with mean 0 and the standard deviation $\sigma_u = 0.25$. The discount rate β is set as 0.95. The firm's production costs are $C_Y(y_t) = 0.4 * y_t + 0.03 * y_t^2$. The firm's inventory costs are $C_N(n_{t-1}) = 0.02 * n_{t-1} + 0.004 * n_{t-1}^2$.

5. We increase the demand uncertainty, σ_u, by 4%[32], from 0.25 to 0.26. Then, based on the above procedures, we re-solve the firms' dynamic problems, other things being equal. We plot the results in the dashed red line in Figure A2.

Figure A2: Beginning-of-year inventory, demand uncertainty, and markup

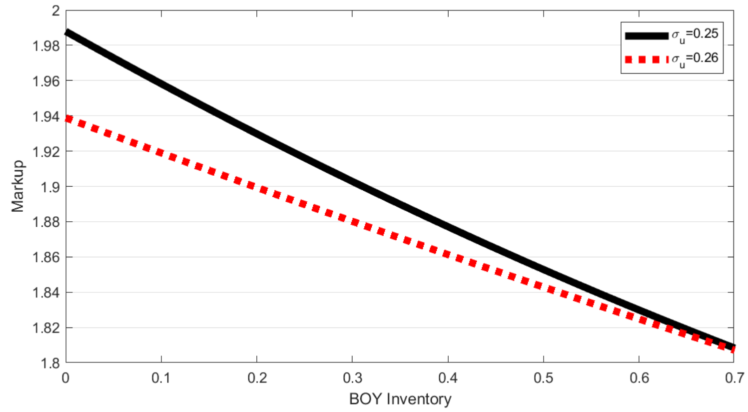


Figure A2 demonstrates the relationships between firm markup, BOY inventory, and demand uncertainty. We can see that a firm's markup decreases in its BOY inventory and demand uncertainty, other things being equal. This numerical analysis provides supporting evidence for Conjecture 1 in the paper.

Then, we simulate the SARS effects based on four scenarios as follows:

1. All firms are unaffected by SARS for all time periods.
2. All firms are affected by SARS at time period $t = 10$, by a one-period temporary negative demand shock.
3. All firms are affected by SARS at time period $t = 10$, by a one-period temporary negative demand shock, and a permanent increase of demand uncertainty in the following periods.
4. All firms are affected by SARS similarly to scenario 3. In addition, after the shock $t \geq 10$, we allow firms to have incentives to change their inventory strategy.

For each scenario, based on the optimal decisions and markup solved on the discretized state grids point by point, we simulate the firm markup up to 45 years for each firm according to the following process:

Step 1: In the first time period, $t = 1$, for all four simulation scenarios, let the firm's state variables, lagged demand shifter and BOY inventory, start from their steady-state values.

Step 2: Given the state variables, ϕ_{t-1} and n_{t-1}, calculate the firm's optimal decisions p_t, y_t, and markup μ_t based on the solutions solved on the discretized state grids.

Step 3: Draw random demand shocks.

3.1 When $1 \leq t < 10$, for all four simulation scenarios, draw random demand shocks, $\widetilde{u}_t \sim \mathcal{N}(0, {\sigma_u}^2)$ where $\sigma_u = 0.25$. Update the demand shifter from ϕ_{t-1} to ϕ_t following (D.2). Based on the firm's decisions p_t, y_t, and the realized $\widetilde{u}_t$, update inventory from

[32]Not that this increase of demand uncertainty is consistent with the SARS effects on demand uncertainty. The SARS epidemic increased affected firms' demand uncertainty by 0.004, representing a 4% increase, given the mean of 0.1.

n_{t-1} to n_t, following (3) and (4).

3.2 When $t = 10$, for scenario 1, still use the arithmetic in step 3.1 to draw random demand shocks and update state variables. Then go back to step 2.

For scenario 2, draw random demand shocks, $\widetilde{u}_t \sim \mathcal{N}(-0.5, {\sigma_u}^2)$ where $\sigma_u = 0.25$, and update state variables. Then go back to step 2.

For scenario 3, draw random demand shocks, $\widetilde{u}_t \sim \mathcal{N}(-0.5, {\sigma'_u}^2)$ where $\sigma'_u = 0.26$, and update state variables. Then go back to step 2, where the solutions of the dynamic problem are solved based on σ'_u.

For scenario 4, draw random demand shocks using the same arithmetic in scenario 3 and update state variables. While, when going back to step 2, the dynamic problem is solved based on the model that allows the firm to have an incentive to change the inventory strategy. The firm will pay an additional cost, $\xi = 0.01$, if it stocks out at time t.[33]

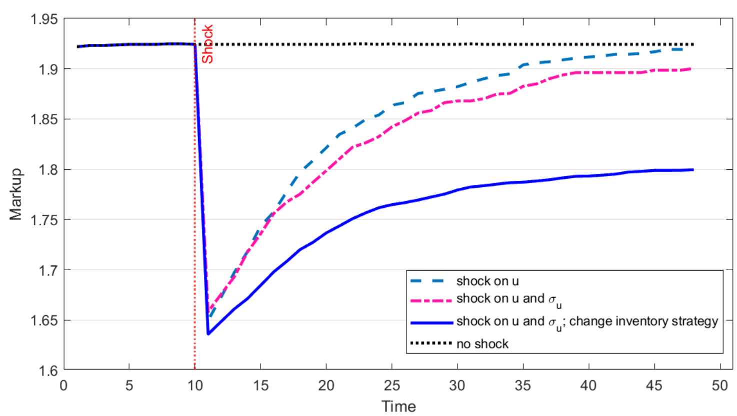
3.3 When $t > 10$, for scenarios 1 and 2, still use the arithmetic in step 3.1 to draw random demand shocks and update state variables. Then go back to step 2.

For scenarios 3 and 4, still use the corresponding arithmetic in step 3.2 to draw random demand shocks, update state variables, and go back to step 2 for solving the dynamic problems.

Step 4: In time period t+1, continue following steps 2 and 3 to update all variables for all firms in different scenarios to the 45 periods.

We simulated 100,000 firms in each time period for each scenario. Thus, in total, we have simulated 18,000,000 observations. The simulation results of SARS effects are shown in Figure A3.

Figure A3: Simulations of SARS effects



Due to the serially correlated demand shifter, after the negative demand shock, the SARS effects on firm markup do not vanish immediately but return to the steady state smoothly and gradually. The increase in demand uncertainty can further enhance the patterns of

[33]In this extended model, the choice specific value function could be revised as $V(a_t, s_t) = p_t \left\{ \int_{-\infty}^{Q_t} [\widetilde{h}(p_t) + \rho_0 + \rho_1 \phi_{t-1} + u_t]\, dG(u_t) + \int_{Q_t}^{\infty} (n_{t-1} + y_t)\, dG(u_t) \right\} - C_Y(y_t) - C_N(n_{t-1}) - \int_{Q_t}^{\infty} \xi\, dG(u_t) + \beta \sum_{s' \in S} V(s'_{t+1}) f(a_t, s_t, s'_{t-1})$, and the dynamic model could be re-solved on the discretized state grids.

long-lasting effects, shifting the firm markup to a lower steady state after the shock. When demand uncertainty increases, the probability of stocking out increases, then the firm has the incentive to change its inventory strategy, increasing the steady state of inventory to a higher level. This reinforces the features of SARS long-term effects, as shown in the solid blue line in Figure A3. Simulations of SARS effects on difference scenarios support that a temporary SARS shock can generate long-lasting effects on market power through the mechanisms of serially correlated demand shifter, increased demand uncertainty, and changes in inventory strategy.

E Alternative Decomposition of SARS effect on Markup

As shown in (10), changes in markup were contributed by raw markup and the non-stockout probability $G(Q_t)$. A linear approximation shows that the raw markup contributes to the total markup by $G(Q_t)/[1-\tilde{\mu_t}^2(1-G(Q_t))]\triangle\tilde{\mu_t}$, which equals 5.06 percentage points for mean firms with $G(Q_t) = 0.839$ and $\tilde{\mu_t} = 1.215$, given $\triangle\tilde{\mu_t} = 4.6$ percentage points as reported in Appendix Table A4. Because in the extreme case of no demand shock and inventory, the stockout probability-related term is always 1, the stockout probability-related term represents the direct contribution of the inventory channel caused by demand uncertainty, which equals 35 percent ($= 1 - 5.06/7.8$) of the decline in markup after SARS. This is in the same order of magnitude as that derived using Baron and Kenny (1986) approach. Admittedly, this approach still does not completely separate the contributions of the inventory and demand uncertainty channel from others, because both the stockout probability and raw markup terms are endogenous. The bottom line is both this approach and the Baron and Kenny (1986) approach point to the importance of the inventory and demand uncertainty channel.

F Appendix Tables and Figures

Table A2: Probit Estimates of Not-Stockout Probability $G(Q)$

	Not Stockout Dummy χ
	(1)
L.Inventory (log)	0.160***
	(0.001)
Capital (Log)	0.025***
	(0.001)
Age (log)	0.060***
	(0.002)
Constant	-0.009
	(0.119)
Firm Ownership Status	YES
Industry Fixed Effects	YES
City Fixed Effects	YES
Year Fixed Effects	YES
Observations	1,324,799
Pseudo R^2	0.120

Note: Standard errors (clustered at the city-industry-year level) are in parentheses.
$\chi_{jt} = 1$ if the firm's inventories of finished goods are greater than 0 at time t and $\chi_{jt} = 0$ otherwise.
* $p < .10$, ** $p < .05$, *** $p < .01$

Table A3: Summary Statistics for the Key Variables

Statistics	Mean	Median	sd
Output Values (log)	10.084	10.002	1.159
Sales Values (log)	10.021	9.943	1.176
Inventory Values (log)	7.641	7.734	1.631
Total Variable Costs (log)	9.902	9.823	1.137
Capital Stock (log)	8.407	8.396	1.538
Inventory Ratio	0.127	0.092	0.117
Predicted Not-stocking Out Prob. $\hat{\psi}$	0.839	0.872	0.120
Demand Uncertainty	0.100	0.098	0.028
Markup μ	1.291	1.230	0.325
Raw Markup $\tilde{\mu}$	1.215	1.187	0.207
Correlation Coefficient between μ and $\tilde{\mu}$	0.902		
Share of Stockout Observations	15.891%		
Observations	1,234,011		

Note: Constructing the inventory ratio and estimating the not-stockout probability and demand uncertainty require data on the beginning-of-year inventory, which is defined as the lagged end-of-year inventory in our analysis. As a result, observations from 1999 to 2007 are used throughout the paper.

Table A4: Robustness Check: Alternative Markup Measures

	(1)	(2)	(3)	(4)
	Markup Based on Costs of Goods Sold			
Treated*SARS	-0.021***	-0.020***	-0.011*	-0.011*
	(0.006)	(0.006)	(0.006)	(0.006)
L.Inventory Ratio			-0.172***	-0.170***
			(0.005)	(0.005)
Demand Uncertainty		-0.188***		-0.065***
		(0.021)		(0.024)
Observations	1,168,488	1,160,924	797,217	792,342
Adjusted R^2	0.102	0.101	0.108	0.107
	Markup Based on the User Costs of Capital			
Treated*SARS	-0.068***	-0.067***	-0.052***	-0.051***
	(0.003)	(0.003)	(0.003)	(0.003)
L.Inventory Ratio			-0.452***	-0.444***
			(0.003)	(0.003)
Demand Uncertainty		-0.503***		-0.268***
		(0.014)		(0.016)
Observations	1,208,534	1,201,133	832,776	827,922
Adjusted R^2	0.119	0.121	0.150	0.151
	Raw Markup			
Treated*SARS	-0.046***	-0.044***	-0.035***	-0.034***
	(0.002)	(0.002)	(0.002)	(0.002)
L.Inventory Ratio			-0.161***	-0.157***
			(0.002)	(0.002)
Demand Uncertainty		-0.223***		-0.149***
		(0.010)		(0.012)
Observations	1,208,577	1,201,194	832,587	827,753
Adjusted R^2	0.125	0.126	0.137	0.138
	Markup Based on Traditional Production Approach			
Treated*SARS	-0.043***	-0.043***	-0.030***	-0.030***
	(0.004)	(0.004)	(0.004)	(0.004)
L.Inventory Ratio			-0.141***	-0.140***
			(0.004)	(0.004)
Demand Uncertainty		-0.107***		-0.029
		(0.018)		(0.020)
Observations	1,204,636	1,197,249	828,506	823,680
Adjusted R^2	0.107	0.107	0.109	0.109

Note: Standard errors (clustered at the city-industry-year level) are in parentheses.
Controlled for firm-level size and export status, city-level export share, population density, and GDP per capita, and the industry, city, and year fixed effects.
Differential time trend between the treatment and control group is controlled for the markup based on costs of good sold.
* $p < .10$, ** $p < .05$, *** $p < .01$

Table A5: Test for Mechanism: The Role of Inventory and Demand Uncertainty

	Markup			
	(1)	(2)	(3)	(4)
Treated*SARS	-0.078***	-0.074***	-0.059***	-0.058***
	(0.003)	(0.003)	(0.003)	(0.003)
L.Inventory Ratio			-0.376***	-0.371***
			(0.004)	(0.004)
Demand Uncertainty		-0.354***		-0.153***
		(0.015)		(0.017)
Observations	1,208,577	1,201,194	832,587	827,753
Adjusted R^2	0.103	0.104	0.121	0.121

Note: Standard errors (clustered at the city-industry-year level) are in parentheses. Controlled for firm-level size (capital) and export status, city-level export share, population density, and GDP per capita, and the industry, city, and year fixed effects.

* $p < .10$, ** $p < .05$, *** $p < .01$

Table A6: Impacts of the SARS Epidemic: Location Heterogeneity

	Markup	Market Share	Inventory Ratio
	(1)	(2)	(3)
Treated*SARS	-0.073***	-0.011***	0.012***
	(0.003)	(0.004)	(0.001)
Neighbor*SARS	0.043***	0.012***	-0.007***
	(0.003)	(0.002)	(0.001)
Observations	1,208,577	67,753	1,208,577
Adjusted R^2	0.104	0.283	0.135

Note: In columns (1) and (3), control variables include the firm-level size (capital) and export status, city-level export share, population density, and GDP per capital, as well as the industry, city, and year fixed effects. Standard errors (clustered at the city-industry-year level) are in parentheses.

Column (2) controls for province-level export share, population density, and GDP per capital, as well as the industry, province, and year fixed effects. Weighted least squares is used and the total number of firms in the province in each 4-digit industry in each year is used as the weight. Standard errors (clustered at the province-industry-year level) are in parentheses.

* $p < .10$, ** $p < .05$, *** $p < .01$

Table A7: Location Heterogeneity: Use a Cleaner Control Group

	Markup	Market Share	Inventory Ratio
	(1)	(2)	(3)
Treated*SARS	-0.082***	-0.012***	0.013***
	(0.003)	(0.005)	(0.001)
Neighbor*SARS	0.042***	0.013***	-0.008***
	(0.003)	(0.003)	(0.001)
Firm Size (K)	YES		YES
Firm Export Status	YES		YES
City/Province Export Share	YES	YES	YES
City/Province Population Density	YES	YES	YES
City/Province GDP per capita	YES	YES	YES
Industry Fixed Effects	YES	YES	YES
City/Province Fixed Effects	YES	YES	YES
Year Fixed Effects	YES	YES	YES
Observations	1,042,374	52,472	1,042,374
Adjusted R^2	0.103	0.259	0.134

Notes: In the first and third columns, firm and city level covariates and fixed effects are controlled. Standard errors (clustered at the city-industry-year level) are in parentheses.

In the second column,province level covariates and fixed effects are controlled. Standard errors (clustered at the province-industry-year level) are in parentheses. Weighted least squares is used and the total number of firms in the province of each 4-digit industry in each year is used as the weight.

Control provinces that share the border with at least one of the four treated provinces but with more than 10 SARS cases are dropped.

* $p < .10$, ** $p < .05$, *** $p < .01$

Table A8: Impacts of SARS Epidemic: Final Goods Industries versus Intermediate Goods Industries

	Inventory Ratio	Demand Uncertainty	Markup			
	(1)	(2)	(3)	(4)	(5)	(6)
Treated*SARS*Final	0.020***	0.005***	-0.080***	-0.075***	-0.056***	-0.056***
	(0.001)	(0.001)	(0.004)	(0.004)	(0.004)	(0.004)
Treated*SARS*Intermediate	0.010***	0.002***	-0.077***	-0.073***	-0.059***	-0.059***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)
L.Inventory Ratio					-0.376***	-0.371***
					(0.004)	(0.004)
Demand Uncertainty				-0.354***		-0.153***
				(0.015)		(0.017)
SARS*Final, Treated*Final	YES	YES	YES	YES	YES	YES
Firm Size (K)	YES	YES	YES	YES	YES	YES
Firm Export Status	YES	YES	YES	YES	YES	YES
City Export Share	YES	YES	YES	YES	YES	YES
City Population Density	YES	YES	YES	YES	YES	YES
City GDP Per Capita	YES	YES	YES	YES	YES	YES
Industry Fixed Effects	YES	YES	YES	YES	YES	YES
City Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Observations	1,208,577	1,201,194	1,208,577	1,201,194	832,587	827,753
Adjusted R^2	0.135	0.394	0.103	0.104	0.121	0.121

Note: Final goods industries: Agriculture Food Processing; Other Food Production; Beverages; Tobacco Products; Textiles; Textile Wearing Apparel, Footwear, Caps; Leather, Fur, Feather & Related Products; Furniture; Paper and Paper Products; Cultural, Educational, Arts and Crafts, Sports and Entertainment Products; Pharmaceutical Products; Artwork.

Intermediate goods industries: Processing of Timber, Articles of Wood, etc.; Printing, Reproduction of Recording Media; Processing of Petroleum, Coke, Nuclear Fuel; Chemicals and Chemical Products; Man-made Fibres; Rubber Products; Plactics Products; Non-metallic Mineral Products; Smelting & Processing of Ferrous Metals; Smelting & Proc. of Non-ferrous Metal; Metal Products; General-purpose Machinery; Special-purpose Machinery; Transport Equipment; Electrical Machinery and Equipment; Comm. Eqpt., Computer & Other Electronic Eqpt.; Measuring Instruments and Machinery for Cultural Activity and Office Work.

Standard errors (clustered at the city-industry-year level) are in parentheses.

* $p < .10$, ** $p < .05$, *** $p < .01$

Table A9: Impacts of SARS Epidemic: High versus Low Demand Uncertainty Industries

	Inventory Ratio	Demand Uncertainty	Markup			
	(1)	(2)	(3)	(4)	(5)	(6)
Treated*SARS*DmdUncertH	0.017***	0.003***	-0.093***	-0.088***	-0.073***	-0.073***
	(0.002)	(0.001)	(0.004)	(0.004)	(0.005)	(0.005)
Treated*SARS*DmdUncertL	0.012***	0.004***	-0.070***	-0.065***	-0.050***	-0.049***
	(0.002)	(0.001)	(0.004)	(0.004)	(0.004)	(0.004)
L.Inventory Ratio					-0.375***	-0.371***
					(0.003)	(0.004)
Demand Uncertainty				-0.351***		-0.153***
				(0.015)		(0.017)
SARS*DmdUncertHigh	YES	YES	YES	YES	YES	YES
Treated*DmdUncertHigh	YES	YES	YES	YES	YES	YES
Firm Size (K)	YES	YES	YES	YES	YES	YES
Firm Export Status	YES	YES	YES	YES	YES	YES
City Export Share	YES	YES	YES	YES	YES	YES
City Population Density	YES	YES	YES	YES	YES	YES
City GDP Per Capita	YES	YES	YES	YES	YES	YES
Industry Fixed Effects	YES	YES	YES	YES	YES	YES
City Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Observations	1,208,577	1,201,194	1,208,577	1,201,194	832,587	827,753
Adjusted R^2	0.136	0.396	0.103	0.105	0.121	0.121

Note: The dummy variable $DmdUncertH_{ind} = 1$ for all years if the industry's mean of demand uncertainty before SARS is higher than the overal mean of demand uncertainty before SARS, and it equals 0 for all years otherwise. The dummy variable $DmdUncertL_{ind}$ is defined as $DmdUncertL_{ind} = 1 - DmdUncertH_{ind}$.

Standard errors (clustered at the city-industry-year level) are in parentheses.

* $p < .10$, ** $p < .05$, *** $p < .01$

Table A10: Impacts of the SARS Epidemic: Firm Sales Heterogeneity

	Markup
	(1)
Treated*SARS	-0.013
	(0.019)
Treated*SARS*ln(Sales)	-0.008***
	(0.002)
SARS*ln(Sales), Treated*ln(Sales), and ln(Sales)	YES
Observations	1,208,402
Adjusted R^2	0.118

Note: Standard errors (clustered at the city-industry-year level) are in parentheses. Control variables include the firm-level size (capital) and export status, city-level export share, population density, and GDP per capital, as well as the industry, city, and year fixed effects.
* $p < .10$, ** $p < .05$, *** $p < .01$

Table A11: Impacts of the SARS Epidemic on the Intermediate Inventory Ratio

	Intermediate Inventory Ratio		
	(1)	(2)	(3)
Treated*SARS	0.005***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)
Firm Size (K)		YES	YES
Firm Export Status			YES
City Export Share			YES
City Population Density	YES	YES	YES
City GDP Per Capita	YES	YES	YES
Industry Fixed Effects	YES	YES	YES
City Fixed Effects	YES	YES	YES
Year Fixed Effects	YES	YES	YES
Observations	1,202,803	1,202,803	1,202,803
Adjusted R^2	0.112	0.124	0.125

Note: Standard errors (clustered at the city-industry-year level) are in parentheses.
* $p < .10$, ** $p < .05$, *** $p < .01$

Table A12: Robustness Check: Firm Fixed Effects

	Inventory Ratio	Demand Uncertainty	Markup			
	(1)	(2)	(3)	(4)	(5)	(6)
Treated*SARS	0.012***	0.003***	-0.052***	-0.052***	-0.041***	-0.040***
	(0.001)	(0.000)	(0.002)	(0.002)	(0.003)	(0.003)
L.Inventory Ratio					-0.190***	-0.189***
					(0.005)	(0.005)
Demand Uncertainty				-0.171***		-0.164***
				(0.015)		(0.018)
Firm Size (K)	YES	YES	YES	YES	YES	YES
Firm Export Status	YES	YES	YES	YES	YES	YES
City Export Share	YES	YES	YES	YES	YES	YES
City Population Density	YES	YES	YES	YES	YES	YES
City GDP Per Capita	YES	YES	YES	YES	YES	YES
Firm Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Observations	1,208,440	1,201,060	1,208,440	1,201,060	832,479	827,645
Adjusted R^2	0.617	0.575	0.357	0.357	0.370	0.370

Note: Standard errors (clustered at the firm level) are in parentheses.
* $p < .10$, ** $p < .05$, *** $p < .01$

Table A13: Robustness Check: Use 6 Provinces as Treatment Group

	Inventory Ratio	Demand Uncertainty	Markup			
	(1)	(2)	(3)	(4)	(5)	(6)
Treated*SARS	0.007***	0.003***	-0.051***	-0.049***	-0.039***	-0.037***
	(0.001)	(0.000)	(0.002)	(0.002)	(0.003)	(0.003)
L.Inventory Intensity					-0.375***	-0.371***
					(0.004)	(0.004)
Demand Uncertainty				-0.351***		-0.151***
				(0.015)		(0.017)
Firm Size (K)	YES	YES	YES	YES	YES	YES
Firm Export Status	YES	YES	YES	YES	YES	YES
City Export Share	YES	YES	YES	YES	YES	YES
City Population Density	YES	YES	YES	YES	YES	YES
City GDP Per Capita	YES	YES	YES	YES	YES	YES
Industry Fixed Effects	YES	YES	YES	YES	YES	YES
City Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Observations	1,208,577	1,201,194	1,208,577	1,201,194	832,587	827,753
Adjusted R^2	0.137	0.394	0.104	0.105	0.122	0.122

Note: Standard errors (clustered at the city-industry-year level) are in parentheses.
* $p < .10$, ** $p < .05$, *** $p < .01$

Table A14: Robustness Check: Uniform Cutoff of Treatment Year in 2003

	Inventory Ratio	Demand Uncertainty	Markup			
	(1)	(2)	(3)	(4)	(5)	(6)
Treated*SARS	0.012***	0.003***	-0.092***	-0.091***	-0.078***	-0.077***
	(0.001)	(0.000)	(0.003)	(0.003)	(0.003)	(0.003)
L.Inventory Intensity					-0.375***	-0.370***
					(0.003)	(0.004)
Demand Uncertainty				-0.354***		-0.153***
				(0.015)		(0.017)
Firm Size (K)	YES	YES	YES	YES	YES	YES
Firm Export Status	YES	YES	YES	YES	YES	YES
City Export Share	YES	YES	YES	YES	YES	YES
City Population Density	YES	YES	YES	YES	YES	YES
City GDP Per Capita	YES	YES	YES	YES	YES	YES
Industry Fixed Effects	YES	YES	YES	YES	YES	YES
City Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Observations	1,208,577	1,201,194	1,208,577	1,201,194	832,587	827,753
Adjusted R^2	0.135	0.394	0.104	0.105	0.122	0.122

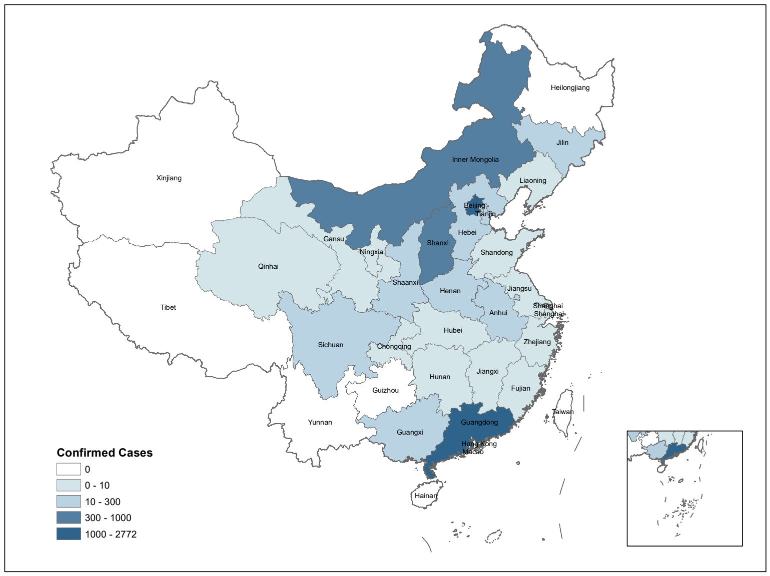
Note: Standard errors (clustered at the city-industry-year level) are in parentheses.
* $p < .10$, ** $p < .05$, *** $p < .01$

Table A15: Robustness Check: Inventory of Finished Goods

	Inventory Ratio	Demand Uncertainty	Markup			
	(1)	(2)	(3)	(4)	(5)	(6)
Treated*SARS	0.014***	0.003***	-0.054***	-0.051***	-0.039***	-0.038***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
L.Inventory Ratio					-0.261***	-0.256***
					(0.004)	(0.004)
Demand Uncertainty				-0.294***		-0.177***
				(0.014)		(0.016)
Firm Size (K)	YES	YES	YES	YES	YES	YES
Firm Export Status	YES	YES	YES	YES	YES	YES
City Export Share	YES	YES	YES	YES	YES	YES
City Population Density	YES	YES	YES	YES	YES	YES
City GDP Per Capita	YES	YES	YES	YES	YES	YES
Industry Fixed Effects	YES	YES	YES	YES	YES	YES
City Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Observations	1,021,722	995,006	1,021,722	995,006	666,758	650,082
Adjusted R^2	0.090	0.349	0.119	0.120	0.131	0.131

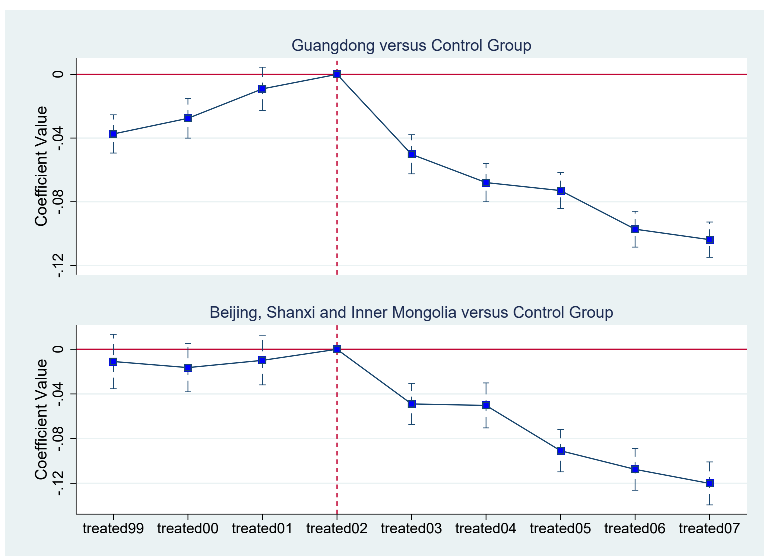
Note: Standard errors (clustered at the city-industry-year level) are in parentheses.
* $p < .10$, ** $p < .05$, *** $p < .01$

Figure A4: Distribution of confirmed cases of SARS infection in China



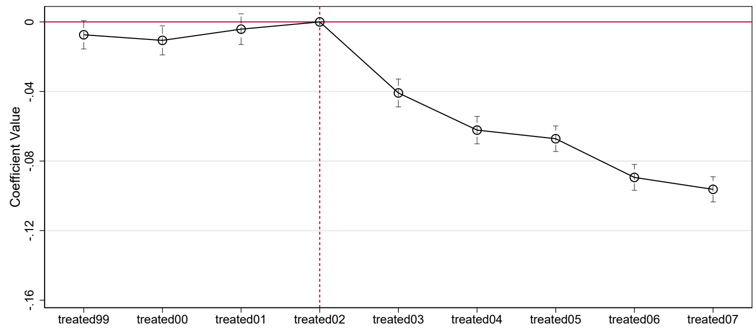
Note: The pattern is similar for the number of deaths from SARS.

Figure A5: Source of the pre-trend of markup



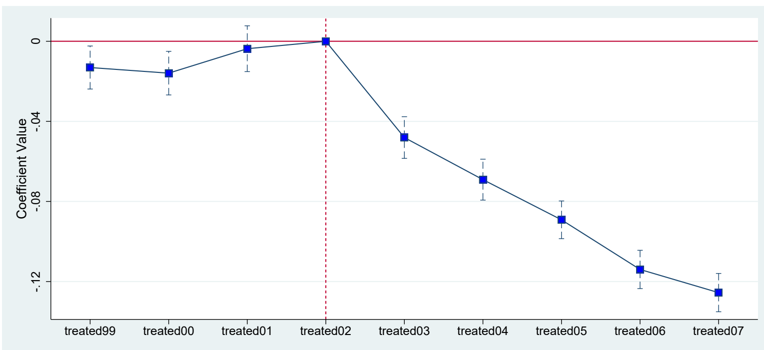
Note: The range represents the 95% confidence intervals of the parameter estimates.

Figure A6: Dynamic effects of SARS on markup (log) : $\beta_{treated*t}$



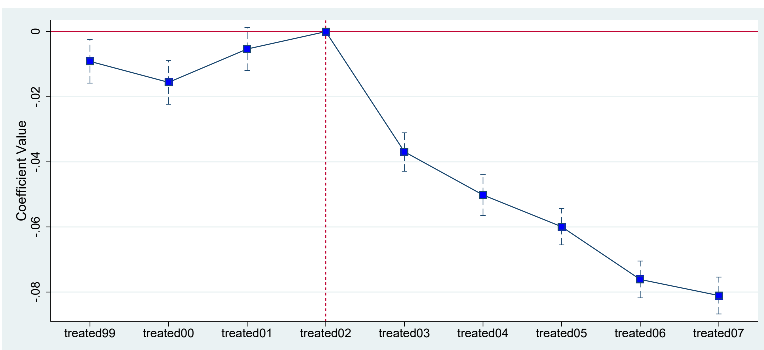
Note: The range represents the 95% confidence intervals of the parameter estimates.

Figure A7: Robustness check for alternative markup measure: Dynamic effects of SARS on markup based on the user costs of capital



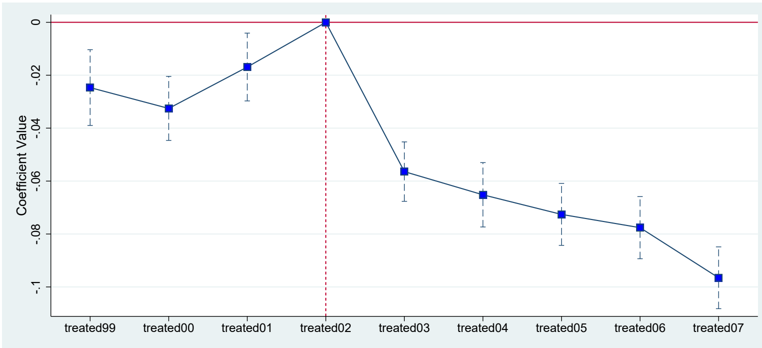
Note: The range represents the 95% confidence intervals of the parameter estimates.

Figure A8: Robustness check for alternative markup measure: Dynamic effects of SARS on raw markup



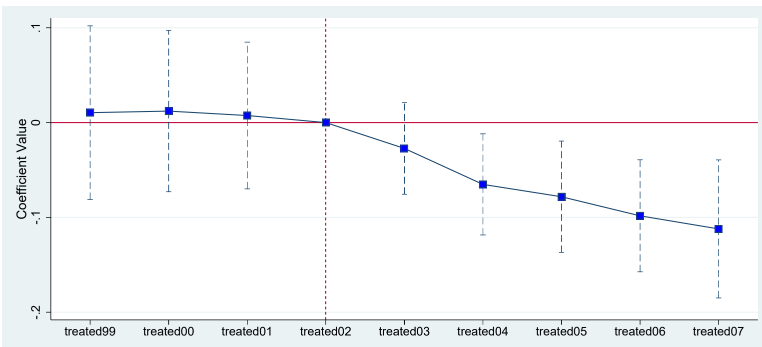
Note: The range represents the 95% confidence intervals of the parameter estimates.

Figure A9: Robustness check for alternative markup measure: Dynamic effects of SARS on markup based on the production approach



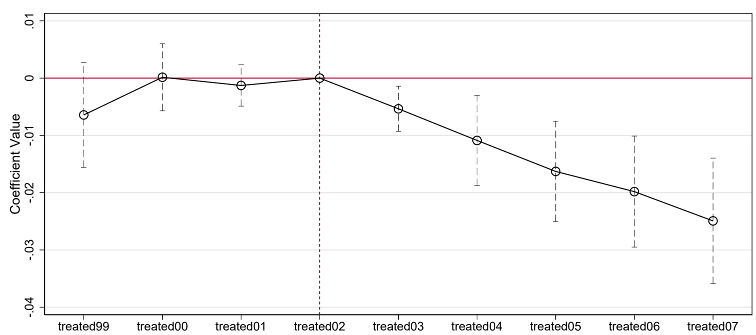
Note: The range represents the 95% confidence intervals of the parameter estimates.

Figure A10: Dynamic effects of SARS on the Producer Price Index: $\beta_{treated*t}$



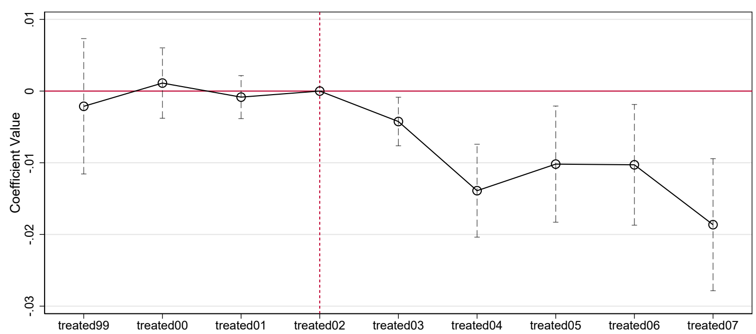
Note: The range represents the 95% confidence intervals of the parameter estimates.

Figure A11: Dynamic effects of SARS on province-industry-level market share: $\beta_{treated*t}$



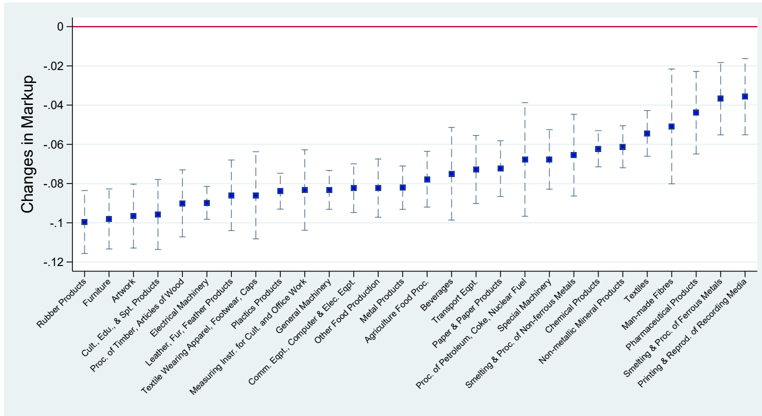
Note: The range represents the 95% confidence intervals of the parameter estimates.

Figure A12: Dynamic effects of SARS on the province-industry-level share of number of firms: $\beta_{treated*t}$

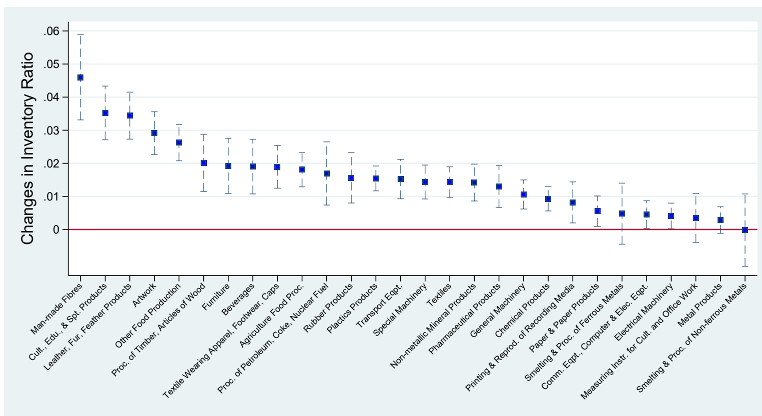


Note: The range represents the 95% confidence intervals of the parameter estimates.

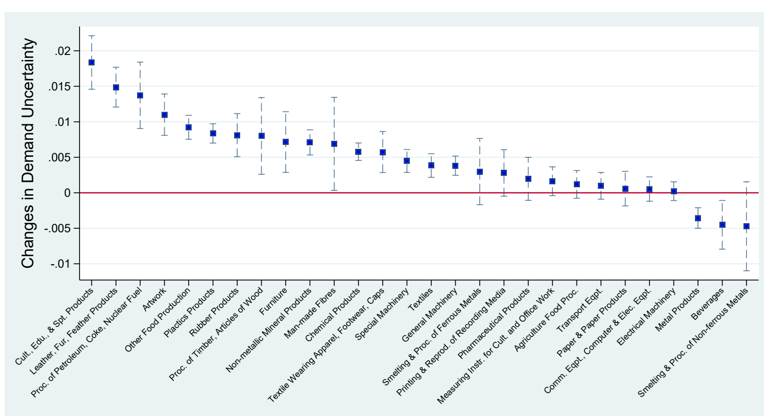
Figure A13: Heterogeneous SARS effects: Different industries



(a) Markup



(b) Inventory Ratio

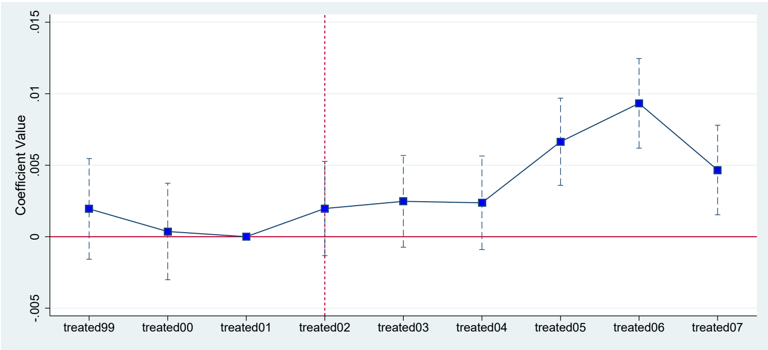


(c) Demand Uncertainty

Note: Results for tobacco products industry are insignificant due to insufficient observations in that industry. The range represents the 95% confidence intervals of the parameter estimates.

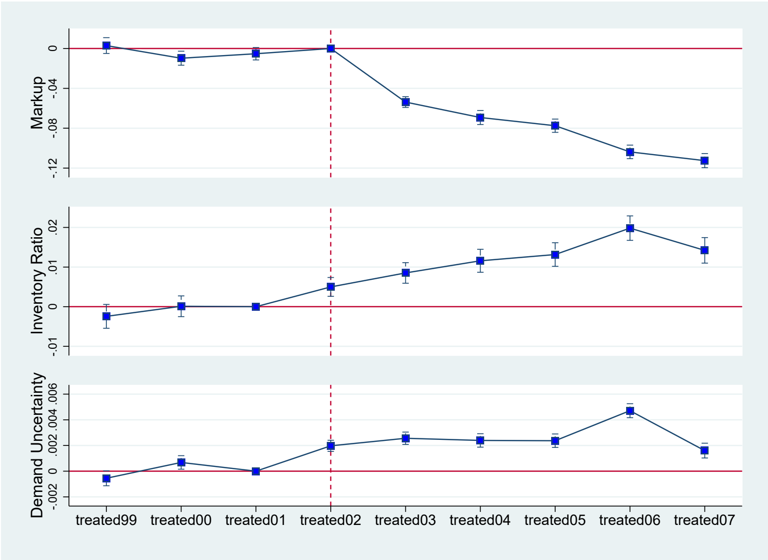
Figure A14: Heterogeneous Impacts of SARS Based on Initial Markup

Figure A15: Dynamic effects of SARS on intermediate inventory ratio



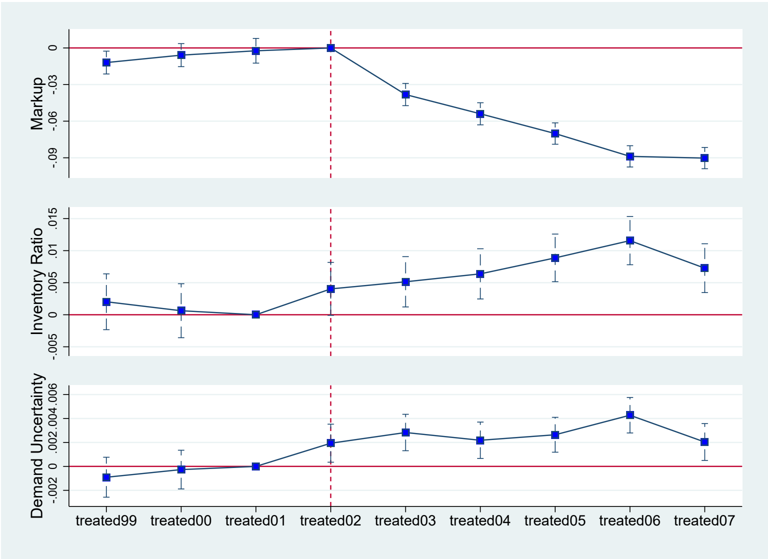
Note: The range represents the 95% confidence intervals of the parameter estimates.

Figure A16: Robustness check for firm fixed effects: Dynamic effects of SARS on markup, inventory ratio and demand uncertainty



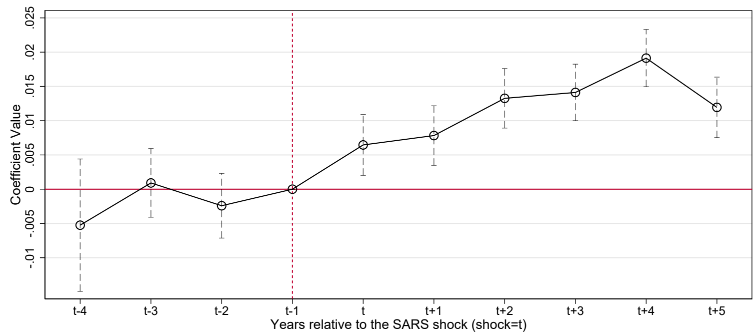
Note: The range represents the 95% confidence intervals of the parameter estimates.

Figure A17: Robustness check for 6 treated provinces: Dynamic effects of SARS on markup, inventory ratio and demand uncertainty

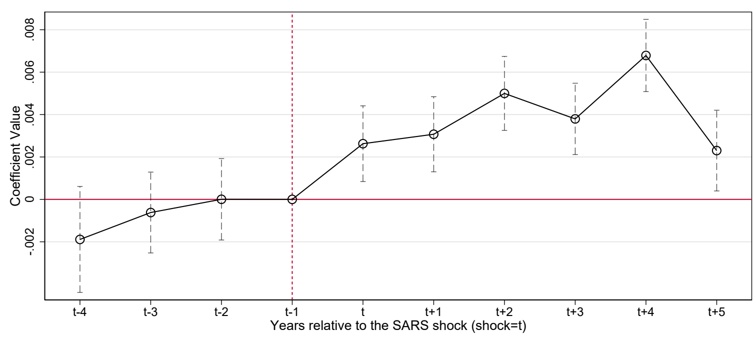


Note: The range represents the 95% confidence intervals of the parameter estimates.

Figure A18: Dynamic effects of SARS on the inventory ratio and demand uncertainty: Based on relative time periods to SARS shock



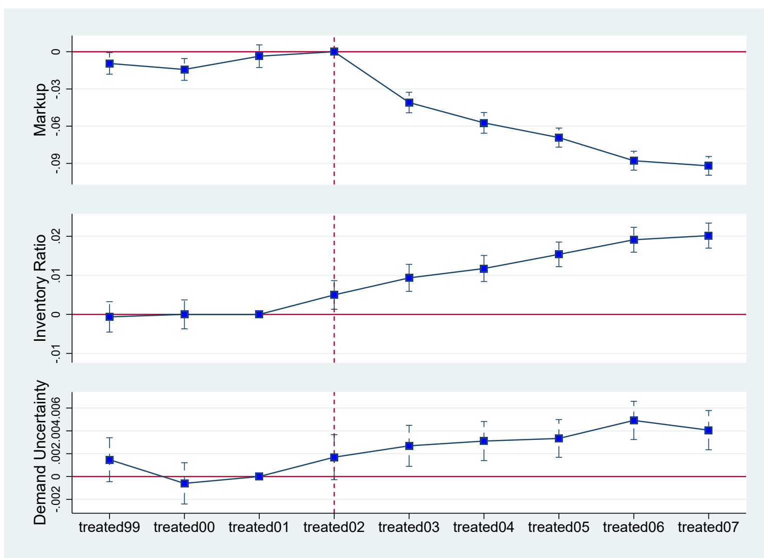
(a) Inventory Ratio



(b) Demand Uncertainty

Note: The range represents the 95% confidence intervals of the parameter estimates.

Figure A19: Robustness check for inventory of finished goods: Dynamic effects of SARS on markup, inventory ratio and demand uncertainty



Note: The range represents the 95% confidence intervals of the parameter estimates.